Essays on Economics of Education:

Perceptions of Returns to Education, Demand for Education, and Subject Choice

Li Lin

Department of Economics

Royal Holloway, University of London

Supervisors:

Professor Arnaud Chevalier

Professor Peter Dolton

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To Xiaomi

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L. L.

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Introduction

This thesis consists of three papers on the economics of education that address different aspects of human capital investment. Paper 1 focuses on junior high school students in poor rural areas in China and investigates their perceptions of returns to schooling. Papers 2 and 3 are in the UK context. Paper 2 studies the determinants of the demand for post-compulsory education, with an emphasis on the role of net college cost and university students' net liquidity. Paper 3 examines the factors affecting subject choice at the undergraduate level, highlighting the effect of field-specific expected earnings.

Paper 1: Rural Students' Financial Literacy and Their Perceptions of Returns to Education

(Joint with Xiaoxiao Wang and Cheng Yuan)

Young people's lack of motivation to study, especially among developing economies, has been the subject of much discussion. In China, nine-year compulsory education is provided for free. Moreover, direct financial aid is offered to poor youths to ease their burden of educational costs. Yet the opinion of "schooling is useless" prevails widely among students in some regions, and poor rural areas have been experiencing high dropouts, especially from junior high schools. One reason could be students' biased perceptions of returns to education, which have been found to be associated with young people's lack of motivation to study. To address these challenges, policy interventions have been utilized to provide students with detailed information about educational costs and benefits. However, plenty of evidence suggests that such informational interventions are not always effective.

This raises the key issue that this paper seeks to address: why do students lack the motivation to study even when they are aware of educational costs and benefits?

From the perspective of behavioral biases, our study explores possible explanations by applying the concept of financial literacy in the context of human capital investment. We investigate the role of one's financial literacy in determining her perceptions of returns to education.

The approach of this paper is two-fold. We start with a theoretical analysis of a two-period model of human capital investment. An important assumption is that students with insufficient financial literacy tend to exhibit a cognitive bias, the "ironing heuristic." This heuristic bias has been extensively studied in the literature on behavioral economics. Under the ironing heuristic, people are prone to linearize complex non-linear payoff schedules. Consequently, they will regard the average rate of the payoff schedule as the marginal rate. In our context, financially illiterate students tend to linearize the nonlinear human capital formation. As a result, they mistakenly perceive the average payoff to their study efforts as the marginal payoff, especially when the educational investment is in the most beneficial phase. This leads to students' underestimation of the marginal return to education and thus insufficient investment in education. The theoretical results suggest two hypotheses that, with lower financial literacy, students would perceive a smaller influence from education on future earnings and also expect lower monetary returns to schooling.

We then proceed to provide empirical evidence of the effect of financial literacy, using survey data collected from four junior high schools in a poor rural county. Specifically, a student's financial literacy is measured by her score of financial knowledge, which is an average of the scores of her financial knowledge of compound interest, inflation, and personal financial investment. The outcome of interest is the perception of returns to schooling. To test the two hypotheses, there are clear rationales for measuring the outcome variable in the following two dimensions: an individual's awareness of educational benefits and her expected labor market payoffs. Our baseline estimations indicate a positive correlation between financial literacy and the perception of educational returns. Moreover, these results hold in various robustness checks. In particular, students with poor knowledge of compound interest are found to perceive lower returns to education, which is in line with our theoretical assumption that poor financial literacy is associated with linearization bias. These findings are also supported by the IV estimations.

In conclusion, both our theoretical and empirical analyses suggest that financial illiteracy biases or impairs students' understanding of returns to education. A key insight is that promoting students' financial literacy can be effective in motivating students to learn at school in poor rural areas.

Paper 2: From Grants to Loans and Fees: The Demand for Post-compulsory Education in England and Wales from 1955 to 2018

(Joint with Peter Dolton)

This paper is motivated by the substantial changes in HE financial arrangements in the UK over the past few decades. With successive reforms, the university system has progressively moved from a free college system to one where individual participants (and their parents) pay a larger share of the costs of their education. Meanwhile, these reforms are accompanied by a sequence of other HE policy changes.

Despite the rising educational cost, participation in post-compulsory education has increased ever since. However, to what extent do the upward trends represent a long-term increase in participation, rather than short-run adjustments? More importantly, what is the impact of the aforementioned policy changes on the demand for post-compulsory education over a long period of time? A time-series analysis would be a good fit in this setting. Yet, to our knowledge, very few time-series studies have been devoted to answering these questions. Our paper fills this gap by exploiting the regime changes in HE funding, using data collected from various sources.

Specifically, this study provides a time-series analysis of the demand for post-compulsory education in England and Wales from 1955 to 2018. We employ Seemingly Unrelated Regressions to model young people's three-stage schooling decisions. We estimate a system of equations of the post-16 staying on rate, the qualified leaver rate, and the university entrance rate. The paper focuses on the effect of HE finance policy changes on the demand for education. To incorporate these policy changes in our estimation, we take account of separate elements of the HE funding reforms and construct two variables that reflect the policy changes: net college cost as well as net liquidity that is available to university students during their studies.

Another contribution of this paper is to account for structural breaks in the time-series analysis. Our analysis is based on time-series data over a time period that saw great variation in the education policy. These data are therefore usually non-stationary due to legislative or structural changes and institutional reforms. For this reason, we account for structural shifts in the stationarity tests of the variables. Furthermore, we estimate our model based on the timing of the structural break points that are explicitly detected for the system of three equations.

The structural break tests indicate that most of the breaks occurred in line with several important policy changes. The estimation results show that net college cost has had a significantly negative but quantitatively small impact on university entrance. On the other hand, the demand for HE appears insensitive to changes in students' net liquidity over the post-reform era. In addition, there are gender differences in the break points, and both the impacts of net college cost and net liquidity vary by gender.

Paper 3: Undergraduate Subject Choice: The Role of Gender, Social Class, and Expected Earnings

When it comes to schooling decisions, students select education not only by level (i.e. number of years of education), as studied in Paper 2, but also by type (i.e. field of study). Sector-specific labor shortage persistently occurs, especially in the new era of emerging technologies, including automation and artificial intelligence. Understanding why an individual chooses a specific field of study may shed light on how to address sector-specific labor shortages.

This paper contributes to the growing literature on the type of education by examining the determinants of subject choice at the undergraduate level. The focus of the study is the role of gender, social class, and individuals' expected earnings in determining college students' choice of fields. Our study is based on individual-level data from the 2004/05 Student Income and Expenditure Survey. Since the survey does not provide information on students' expectations about earnings at the time of choosing fields of study, we use exogenous income data to calculate the earnings of earlier cohorts. This is then used as a proxy for the expected earnings of the cohort under study.

We first discuss characteristics of subject choices based on descriptive statistics. The analysis suggests gender gaps in subject choices. We then proceed to estimate a multinomial logit model of students' subject choice. The estimation results highlight evident and consistent gender segregation across disciplines. In line with what the descriptive statistics suggest, female students tend to choose Arts and Humanities but are more likely to avoid STEM-related fields. Socio-economic gaps are also found in the choice of subject. Compared to the lowest SES group, children of higher social class tend to opt for Arts and Humanities. In addition, female students of the lowest SES group appear to be least inclined to select Engineering and Applied Subjects, compared with their male counterparts of the same social class or females in other higher SES groups.

Finally, expected earnings are found to be positively correlated with the probability of choosing Professional Subjects or Engineering and Applied Subjects, whereas the opposite applies to the choice of the remaining three subject groups: Science, Social Science, and Arts and Humanities. These findings indicate the importance of accounting for non-pecuniary factors when examining the choice of field of study.

The rest of this thesis presents these three papers.

Rural Students' Financial Literacy and Their Perceptions of Returns to Education*

(Joint with Xiaoxiao Wang and Cheng Yuan)

Abstract

This paper studies how students' financial literacy affects their perceptions of returns to education and consequently their schooling decisions. We first propose a model of human capital accumulation where financially illiterate students exhibit a cognitive bias of "ironing" heuristic. With this decision heuristic, students tend to linearize the relationship between educational investments and future earnings, resulting in an underestimation of returns to education and thus inadequate study efforts. Using survey data from four rural junior high schools in Southwest China, we find a positive correlation between financial literacy and students' perceptions of returns to education, supporting the assumption in the theory. Our findings suggest that promoting students' financial literacy can be an effective policy to motivate students to learn at school, especially in poor rural areas.

Key words: Financial literacy; Ironing heuristic; Educational investment; Returns to education
JEL: D14, D91, I26, J24

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1 Introduction

It is well known that students' perceptions of educational benefits and costs exert a considerable influence on their schooling decisions. Many studies have found that a biased perception of returns to education can contribute to the lack of motivation to study (e.g., Jensen, 2010; Attanasio and Kaufman, 2014). One possible remedy for such a misperception is to provide students (and their parents) with a range of tailored information, including that of schooling costs, financial aid opportunities, and future earnings. There has been fast-growing literature on this important informational intervention policy (e.g., Lavecchia et al., 2016; Damgaard and Nielsen, 2018).

However, the evidence on the effectiveness of informational interventions remains mixed so far in the literature. Positive evidence is reported in, e.g., Nguyen (2008), Jensen (2010), Hastings et al. (2015), Wiswall and Zafar (2015), McGuigan et al. (2016), and Peter and Zambre (2017). On the other hand, many experimental studies in both developing and developed countries have found no statistically significant effects of informational interventions on school enrollment or completion. For instance, Busso et al. (2017) provided twelfth-grade students in Chile with information about financial aid and returns to specific career-school programs, but this intervention did not affect the extensive margin of enrollment. Kerr et al. (2020) found no significant impact on the post-secondary education enrollment in Finland from informing high school graduates of the earning distribution and employment rates for different post-secondary degrees. Fryer (2016) examined an intervention in the US by sending middle school students daily text messages with information about financial and non-financial benefits of education. He found a positive effect on the awareness of benefits but no effects on state test scores or student study efforts at least in the short term. Similar findings for the US are reported in Carrell and Sacerdote (2017).

This paper first applies the concept of financial literacy to provide a possible explanation of why informational interventions are sometimes ineffective.[1] The key component in our theory is that if students (or their parents) are financially illiterate, then even if they are fully informed of the costs and benefits of schooling, they are still subject to

[1]Generally, financial literacy refers to the knowledge and skills an individual possesses that allow her to make effective decisions regarding financial resources. It involves the "ability to process economic information and make informed decisions about financial planning, wealth accumulation, debt, and pension" (Lusardi and Mitchell, 2014; OECD, 2017).

a cognitive bias, the "ironing" heuristic, when they estimate returns to education. As we will review in detail in Section 2.2, this ironing heuristic, as introduced in Liebman and Zeckhauser (2004), is well documented in the behavioral economics literature. Its essential idea is that people tend to linearize complex non-linear schedules and regard the average rate as the marginal rate in decision-making. In our context, the relationship between the costs and returns of educational investment is typically non-linear (Kail and Ferrer, 2007; Murre, 2014). Under the ironing heuristic, students mistakenly believe that the marginal payoff of their study efforts is given by the average payoff. They will then underestimate returns to schooling, especially when the actual marginal return rate is increasing (i.e., when the educational investment is in the most beneficial phase). Due to this misperception, students will make insufficient study efforts, diluting the potential benefit of informational interventions. We formalize this idea in a two-period model of human capital investment.

Another contribution of the paper is to provide empirical evidence that students' financial literacy indeed influences their perceptions of returns to education. We conducted a survey among four junior high schools in a poor county in Southwest China. Based on the survey data, our analysis shows that financially literate students are more likely to agree that investing in education will increase their future earnings. These students also expect higher monthly incomes in the future. This is consistent with our assumption that financially illiterate students are more prone to the ironing heuristic and tend to linearize the marginal rate of returns to education. In addition, we find that not all financial knowledge has the same impact on students' perceptions of returns to schooling. Although knowledge about compound interest enhances one's expectation of educational returns as well as future earnings, knowledge about inflation, for example, has no such effect.

This paper is also motivated by the issue of high dropouts in remote and poverty-stricken areas in China.[2] Despite the requirements of nine-year compulsory education and relevant policies that provide financial assistance to underprivileged students, independent surveys have reported that the school dropout rate remains high, especially in poor rural areas. For instance, based on eight surveys covering 24,931 students in

[2]These areas include, for example, Bijie city in Guizhou Province, Nujiang of the Lisu Autonomous Prefecture in Yunnan Province, and Liangshan Yi Autonomous Prefecture in Sichuan Province. See, e.g., http://www.gov.cn/zhengce/2017-09/05/content_5222840.htm for discussions on school dropouts in these areas.

four provinces from 2019 to 2013, Shi et al. (2015) show that the three-year cumulative dropout rate in grades seven through nine ranged from 17.6% to 31%.[3] Our research suggests that in addition to providing financial aid, improving students' (and perhaps also their parents') financial literacy can be an effective complementary approach to encouraging students to stay at school.

Our paper also contributes to the growing literature on how financial literacy affects decision-making. Existing research finds supporting evidence that financial literacy helps, for example, household financial sophistication, personal portfolio investment, and accumulation of wealth (Xu and Zia, 2012; Lusardi and Mitchell, 2014; Bongini et al., 2015). However, there is little research on the impact of financial literacy on educational investment. To the best of our knowledge, this paper is the first to address this issue and examine how financial literacy influences an individual's perception of educational returns and schooling decisions.

The remainder of this paper is organized as follows. Section 2 presents a two-period model of human capital investment and formalizes the idea of how the ironing heuristic can lead to suboptimal educational investments. Section 3 describes our data sources and provides descriptive statistics of the main variables. Section 4 reports the empirical results on the relationship between financial literacy and the perception of returns to education. Section 5 concludes and discusses possible policy implications of our research.

2 Theoretical Background

This section studies a two-period model of human capital investment. Our main assumption is that when a student is financially illiterate, she will be subject to the "ironing" heuristic when she makes her study effort choice. We will give a detailed discussion of the literature on the ironing heuristic after presenting the model.

[3]There is lots of similar evidence on high dropout rates in poverty areas in China. For instance, an independent survey conducted across four rural counties found that the cumulative dropout rate over grades seven and eight was as high as 14.2% and estimated that 23% of students dropped out before completion of junior high school (Yi et al., 2012). Similarly, another survey found a high cumulative grades seven and eight dropout rate (19.5%), suggesting a dropout rate of 25% over the three-year secondary education (Chang et al., 2016). Using data from an annual survey of rural households in more than 100 villages across 30 provinces, Liu and Rozelle (2020) suggested that the dropout rate from junior high schools reached 14% overall and was especially high in some of the poorest areas. See also Mo et al. (2013), Yi et al. (2015), Gao et al. (2019), and Yi (2021).

2.1 The Model

Consider a student who lives for two periods. She derives utility $u(c_i)$ in period $i = 1, 2$ if her consumption in that period is c_i. The utility function $u(\cdot)$ is assumed to be twice continuously differentiable, strictly increasing, and concave. Let β be her discount factor.

In the first period, the student attends school with a fixed amount of allowance y from her parents to cover the non-tuition expenses in that period. She has two choices to make: her consumption c_1 (in which case her savings will be $y - c_1$), and her study effort e. (More broadly, we interpret e as a joint product of the length of her schooling, which is determined by whether and when to drop out of school, and how hard she studies while she is in school.) If her effort choice is e, she will possess human capital $f(e)$ when she leaves school and joins the labor market in the second period.[4] Here $f(e)$ is referred to as the function of human capital formation.[5] We assume that $f(0) = 0$ and $f'(e) > 0$, i.e., the student's human capital increases with her study effort. Denote by $v(e)$ the student's effort cost function, and it is assumed to be twice continuously differentiable, strictly increasing, and convex.

Drawing upon the literature on learning curves starting from Mazur and Hastie (1978), we assume that the human capital formation function $f(e)$ is *S-shaped*, i.e., it is first convex and then concave as illustrated in Figure 1 below. It captures the idea that human capital accumulation has a stage of increasing returns in the beginning, followed by a phase of decreasing returns.[6]

In the second period, the student graduates from school (or drops out of school) and

[4]For simplicity we have assumed that human capital is determined solely by the student's effort choice. More generally, other factors such as financial conditions and parental tutoring should also matter for human capital accumulation, but these are perhaps less relevant for students from poor areas in our study.

[5]In the model we assume no uncertainty in the return to education. With uncertainty, $f(e)$ can be interpreted as the expected return to education (or the certainty equivalence if risk aversion matters); the predictions from the model will remain qualitatively the same.

[6]Mazur and Hastie (1978) first propose the concept of S-shaped learning curves. They also provide psychological experiment evidence that an accumulation model with S-shaped learning curves predicts better than the negative exponential growth model of the learning process. This concept has been supported by many subsequent works such as Kail and Ferrer (2007), Leibowitz et al. (2010), and Murre (2014). In our context, S-shaped learning curves well capture the realistic learning pattern that students accumulate knowledge and skills at an increasing speed in the beginning (e.g., because the basic knowledge is relatively easy to learn but is very useful for their future jobs), but then enter a slow-down phase (e.g., because the knowledge becomes more advanced and so harder to learn).

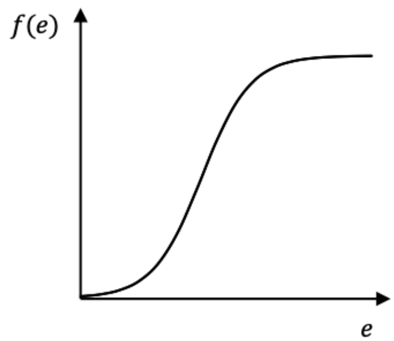


Figure 1: Human Capital Accumulation: An S-Shaped Curve

enters the labor market. When her accumulated human capital from the first period is $f(e)$, we assume that she makes an income $f(e)w$ in the second period, where w is the market wage rate (for per unit of human capital). Since w does not play a critical role in our analysis, we henceforth normalize it to 1. Then the student's consumption in the second period is simply $c_2 = (1+r)(y-c_1)+f(e)$, where r is the interest rate for the first-period savings.

The student aims to maximize her lifetime utility

$$u(c_1) - v(e) + \beta u((1+r)(y-c_1)+f(e))$$

by choosing her consumption c_1 and study effort level e in the first period. To deliver our main message in the most transparent way, we further simplify our model by assuming the allowance from the parents is so limited that it is impossible to save money in the first period (i.e., $c_1 = y$).[7] Then the student's problem is simply to maximize

$$u(y) - v(e) + \beta u(f(e)) \tag{1}$$

by choosing her study effort in the first period.

As a benchmark, suppose first that the student is perfectly rational and accurately understands the function of human capital formation $f(e)$. Then the optimal study

[7]This is a plausible assumption for students in the poor rural areas in China. Also, for students in those areas it is unlikely to take on debt to finance education in period 1, so we assume away the possibility of borrowing in the first period.

effort e^* is determined by the first-order condition

$$v'(e^*) = \beta \cdot u'(f(e^*))f'(e^*), \tag{2}$$

where the left-hand side is the marginal cost of making an effort, and the right-hand side is the (discounted) marginal utility in the second period from making an additional effort in the first period.[8]

2.2 The Ironing Heuristic and Financial Illiteracy

People tend to simplify complicated decision problems by resorting to decision heuristics (e.g., Stanovich, 2003; Berthet, 2022). In our context, the non-linear human capital formation function $f(e)$ is not easy for all students (or their parents) to understand and take into account when they make decisions about human capital investment. Instead of calculating the marginal return to study effort from the actual $f(e)$, students, especially those who are financially illiterate, may linearize the relationship between efforts and human capital accumulation and use the "average" rate to simplify their decisions. This decision heuristic is called the "ironing" heuristic, a cognitive bias well documented in the behavioral economics literature.

Liebman and Zeckhauser (2004) define the "ironing" heuristic as a misperception of complex nonlinear payoff schedules such as pricing schedules, tax schemes, and welfare systems. It arises when a decision-maker perceives the slope of a line segment between the origin and a point on a nonlinear schedule as her average incentive. For example, when facing a progressive tax schedule, a taxpayer may linearize it and use the average income tax rate to decide her optimal effort in earning income. This ironing heuristic has been widely observed in empirical research on income taxes (de Bartolome, 1995; Liebman and Zeckhauser, 2004; Feldman, Katuščák, and Kawano, 2016; Rees-Jones and Taubinsky, 2020). For example, Rees-Jones and Taubinsky (2020) find that the ironing heuristic is prevalent among taxpayers, with about 43% of them ironing. A special case of the ironing heuristic is the so-called "exponential growth bias" in financial decision-

[8] The first-order condition is also sufficient for the optimal solution if the objective function (1) is concave in e, i.e., if $v''(e) \geq \beta w[u'(\cdot)f''(e) + u''(\cdot)w(f'(e))^2]$. This condition is satisfied for the concave part of the function of human capital formation, and it is also satisfied for the convex part if the cost function $v(e)$ is sufficiently convex. For simplicity, we henceforth assume the objective function is concave.

making (Stango and Zinman, 2009; Almenberg and Gerdes, 2012; Levy and Tasoff, 2016; Mckenzie and Liersch, 2019). It accounts for people's tendency to linearize exponential functions. For example, Almenberg and Gerdes (2012) and Mckenzie and Liersch (2019) find that, without a proper understanding of compound interest, participants in their experiments are prone to believe that savings grow linearly and thus underestimate the exponential growth of lifetime earnings. This suggests that the tendency to adopt the ironing heuristic is correlated with a lack of financial literacy.

Although we are not aware of any direct evidence of the ironing heuristic in educational investment decisions, the extensive evidence from other contexts suggests that adopting this heuristic in scenarios involving non-linear payoff schedules is a general tendency in the population, especially among people with poor financial literacy. Consequently, in this paper we assume that financially illiterate students exhibit the ironing heuristic when choosing their study efforts. More specifically, we assume that a financially illiterate student makes a linear estimate of the marginal return to study effort: $k = \frac{f(e^*)}{e^*}$, where e^* is the optimal effort choice made by a perfectly rational student. (One possible justification for observing the optimal choice is that schools may advise students to act optimally by showing them the future income they could earn if they made the optimal effort now.) Given this misperception, the student expects a future income $y_2 = ke$ if she chooses an effort level of e. Then the first-order condition of the utility maximization problem becomes

$$v'(\tilde{e}) = \beta k \cdot u'(k\tilde{e}), \tag{3}$$

where $\tilde{e}$ denotes the "optimal" effort choice under the ironing heuristic.

Figure 2 below illustrates how the ironing heuristic works. Ray k_a is the linear relationship perceived by a financially illiterate student after observing the outcome $(e_1, f(e_1))$ or $(e_2, f(e_2))$, while ray k_b is associated with the outcome $(e_0, f(e_0))$. Notice that $(e_0, f(e_0))$ is the only tangent point between a ray from the origin and the S-shaped function of human capital formation; at that point $f'(e_0) = \frac{f(e_0)}{e_0}$. It is then straightforward to see when $e^* < e_0$, $\frac{f(e^*)}{e^*} < f'(e^*)$; while when $e^* > e_0$, $\frac{f(e^*)}{e^*} > f'(e^*)$. This implies that after observing $(e^*, f(e^*))$, the student will underestimate (overestimate) the marginal return of study effort if $e^* < e_0$ ($e^* > e_0$).

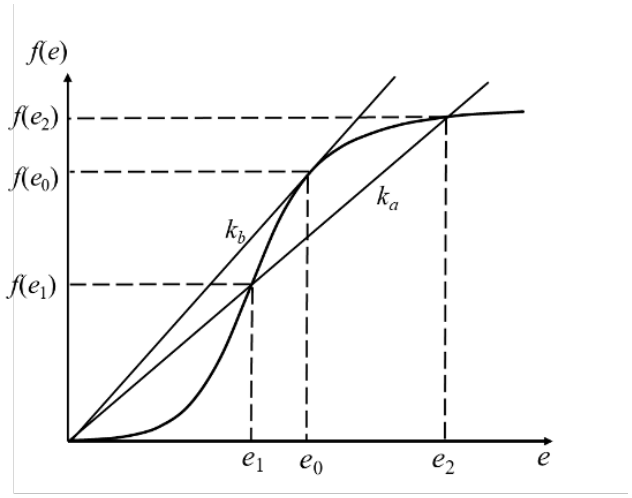


Figure 2: Ironing Heuristic in Estimating the Relationship Between Efforts and Incomes

2.3 Insufficient Effort Choice

We now compare e^*, the optimal study effort by a perfectly rational student with sufficient financial literacy, with $\tilde{e}$, the study effort chosen by a student with poor financial literacy. Using (2) and (3), we get

$$\frac{v'(e^*)}{v'(\tilde{e})} = \frac{u'(f(e^*))}{u'(k\tilde{e})} \frac{f'(e^*)}{k}. \tag{4}$$

Recall that when a student with low financial literacy observes e^*, she infers a constant marginal return to study effort $k = \frac{f(e^*)}{e^*}$. Substituting this into (4) yields

$$\frac{v'(e^*)}{v'(\tilde{e})} = \frac{u'(f(e^*))}{u'(\frac{f(e^*)}{e^*} \cdot \tilde{e})} \cdot \frac{f'(e^*)}{\frac{f(e^*)}{e^*}}. \tag{5}$$

Then we have the following result:

Proposition 1. *Compared to a student with sufficient financial literacy, a financially illiterate student chooses a lower level of study effort (i.e., $\tilde{e} < e^*$) if and only if she observes $e^* < e_0$.*

Proof. Consider first the case when the student observes $e^* < e_0$. Suppose in contrast $\tilde{e} > e^*$. Then we must have $\frac{v'(e^*)}{v'(\tilde{e})} < 1$ given $v'' > 0$. On the other hand, we have (i) $\frac{f(e^*)}{e^*} \cdot \tilde{e} > f(e^*)$, which implies that $\frac{u'(f(e^*))}{u'(\frac{f(e^*)}{e^*} \cdot \tilde{e})} > 1$ given $u'' < 0$, and (ii) $\frac{f(e^*)}{e^*} < f'(e^*)$

and so $\frac{f'(e^*)}{f(e^*)/e^*} > 1$, given $e^* < e_0$. Hence, the left-hand side of condition (5) is strictly less than 1, while the right-hand side is strictly greater than 1. This is a contradiction. A similar logic implies that $\tilde{e} > e^*$ if the student observes $e^* > e_0$. □

This result is simply because when $e^* < e_0$, compared with a student with sufficient financial knowledge, a financially illiterate student underestimates the marginal effect of study effort on her future income. While when $e^* > e_0$, the student overestimates that effect.

Since this paper focuses on students from poverty-stricken regions, presumably they face a sufficiently high marginal cost of making effort (or staying at school).[9] As a result, it makes more sense to assume that their optimal study effort e^* is below e_0. That is, their study effort choice, even if they are rational, is likely to be at the phase of increasing returns. This, together with Proposition 1, implies that relative to financially literate students, financially illiterate students tend to perceive a lower marginal return to education, exert less study effort, and expect a lower income in the future.

We therefore have the following hypotheses for students in poor rural areas:

Hypothesis 1. *Students with lower financial literacy expect a smaller impact of educational attainment on their future earnings.*

Hypothesis 2. *Students with lower financial literacy expect a lower monthly income in the future.*

From the next section, these two hypotheses will be tested by using survey data from four junior high schools in a county in Southwest China.

3 Data and Variables

3.1 Data Collection and Survey Design

The data in our empirical analysis was collected in July 2018, from a hybrid questionnaire survey conducted online-offline at M County in Southwest China, as part of the *Peking University Caitong EconEdu for Kids* Program.[10]

[9]For example, this can be due to the poor education condition in those areas, having little parental tutoring, and the need to help parents especially during farming season.

[10]The *Peking University Caitong EconEdu for Kids* Program is a voluntary program that offers free short-term courses on financial knowledge in rural schools, with the aim of improving rural children's

Located in an autonomous prefecture of Yunnan Province, M County is one of the nationally designated poor counties, featuring the highest poverty rate in the autonomous prefecture and a large outflow of migrant workers. Over 90 percent of the area of the county is mountainous and 85 percent of the population lives in rural areas. The county was designated as a "state-poverty-county" at the time of the survey; according to the official statistics, the annual per capita disposable income of rural residents was less than 11,000 renminbi (RMB) in 2017. Besides, about forty-two percent of the low-wage population in M County migrate to urban areas for higher paid work, leaving their children behind in the care of relatives. In this sense, M County is a representative sample of the poor rural areas in question.

Due to slower economic growth, county-level investments in compulsory education have been low in M County. As a result, the county has been experiencing high dropouts, especially from junior high schools. Specifically, the average graduation rate among the eight rural junior high schools in the county was 86.7 percent in 2017, which was 3.6 and 8.2 percentage points lower than that of the autonomous prefecture and the country, respectively.[11]

The project team randomly chose four out of the eight rural junior high schools in M County. Figure 3 shows the locations of these four schools.[12] The 43 surveyed classes, out of 74 classes in these four schools and 166 classes in the county, were determined by cluster sampling to reduce inter-group differences. And the data collection was led by the survey team members, with the help of the IT instructors who were trained to fully understand the questions and procedures before they were assigned to the classes. The survey sessions were conducted in class under the guidance of IT instructors. In each classroom, participants were provided with an online questionnaire; the IT instructor guided them to complete the questionnaire, typically within 40 minutes. Participants were allowed to seek help from the instructor if they had difficulty in understanding the survey questions. After they completed the questionnaire, all the responses were submitted to the online survey platform. This combination of online-offline procedures

financial literacy. Our survey was completed before the students in our sample enrolled into the finance courses. Therefore, sample contamination should not be an issue for the survey data.

[11] Appendix A provides more details regarding the variation in the junior high school gross enrollment ratio, graduation rate, and promotion ratio of graduates in M County in 2017, compared to the autonomous prefecture where the county is located and the whole country.

[12] As can be seen in Figure 3, the four schools are located roughly in the same line on the map. The distance between adjacent schools varies between 10 and 22 kilometers.

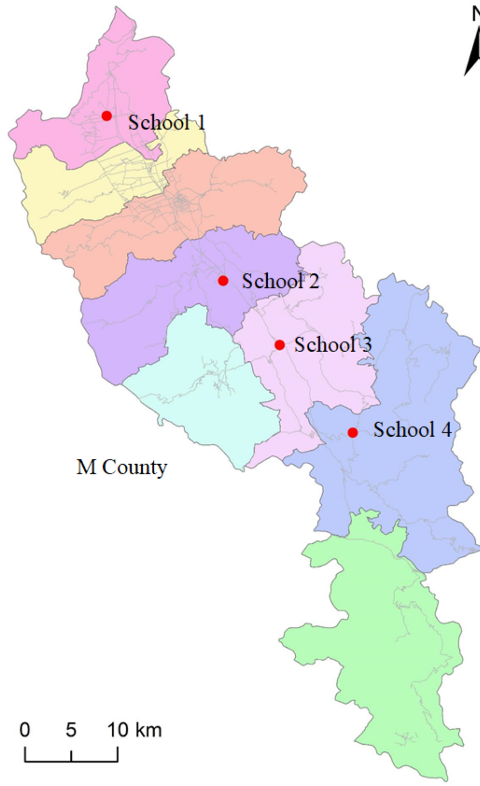


Figure 3: Map of Surveyed Area

guaranteed the quality and efficiency of the data collection. The survey collected 1,737 valid responses in total.

The questionnaire consisted of multiple-choice questions which were designed to be short, specific, and easy to understand, with examples and explanations provided where necessary. The survey design was motivated by existing behavioral economics research on financial decision-making. In addition to demographic characteristics, the survey questions collected data about participants' financial literacy and their perceptions of returns to education. As such, the data set contains a broad range of variables relating to (i) basic personal information and family background; (ii) financial knowledge measured by the understanding of compound interest, inflation, and financial investment; (iii) financial behavior in terms of budget planning and saving; (iv) perceptions of returns to education, approximated by attitude towards educational returns and expected future earnings; and (v) perceptions of costs of schooling, measured by the self-assessed cost of staying on at school.

3.2 Descriptive Statistics

3.2.1 Dependent Variables

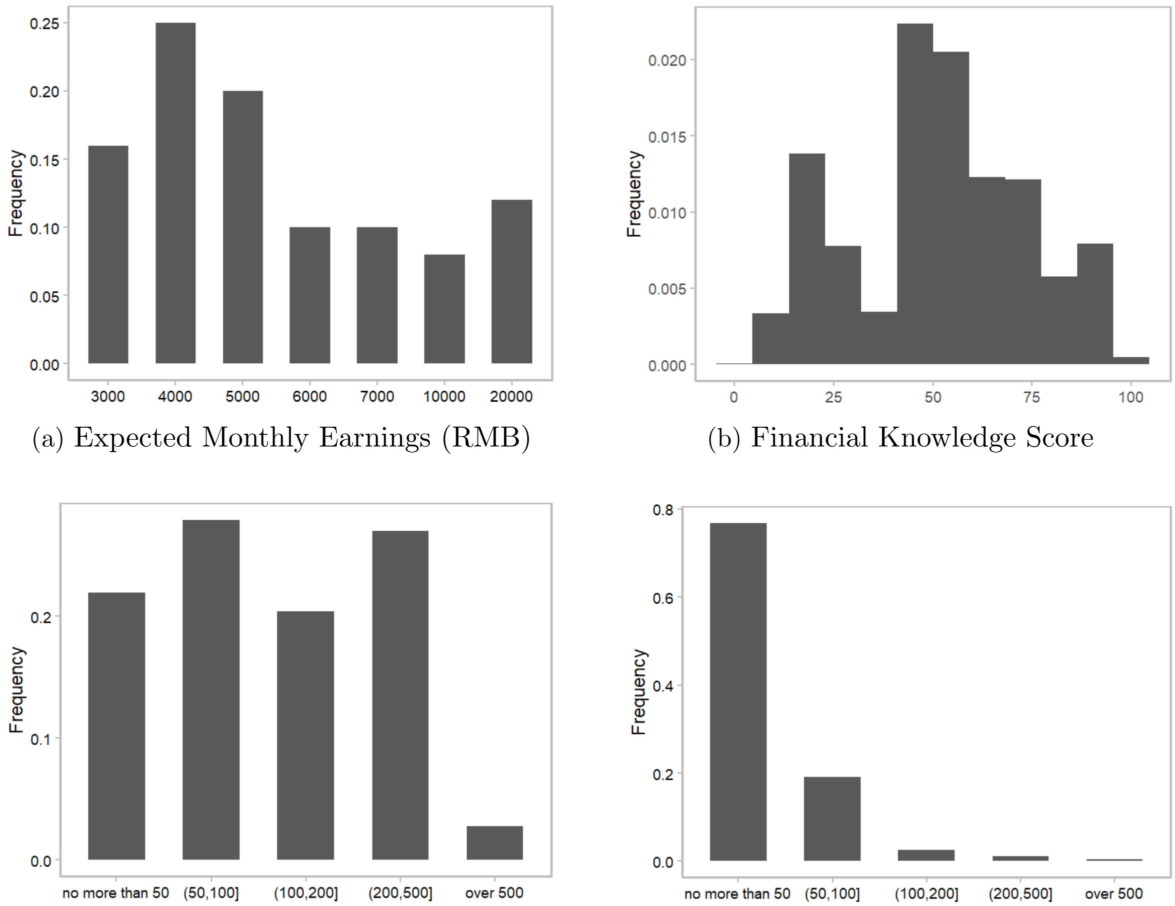
The main outcome of interest in this paper is students' perceptions of returns to schooling. We employ two variables to measure different aspects of an individual's perceptions of education returns: her awareness of educational benefits and her expectation of monthly salary. We first approximate the awareness of educational benefits with the belief that one's future earnings increase with her educational attainment. Students were asked how they agree on a set of related statements,[13] and our data show that 68.11 percent of the respondents agree that earnings increase with one's educational attainment.

We use the expected monthly earnings in twenty years' time to quantify students' expectations of their future earnings. The responses of the interviewed students are shown in Figure 4a. About 25 percent of respondents expect to earn 4,000 RMB per month in twenty years. The average expected earnings amount to 6,874 RMB, much higher than the average monthly income in M County (around 1,000 RMB). Interestingly, the median expected monthly income is 5,000 RMB, same as the reference salary of a college graduate as in the questionnaire.

There are two rationales for measuring students' expected earnings in twenty years' time. First, roughly speaking, a student's age in twenty years will be close to her parents' ages at the time of survey. As such, participants can use their parents' current level of income as a reference point and base their expectations of earnings on it. Second, most of the sampled students were aged 14 to 16 during the survey. In twenty years' time, their earnings growth is likely to enter a relatively stable phase in their mid-career (see, for example, Figure 2 in Paper 3 of this thesis); so do the gaps in earnings across different educational attainments. Therefore, it makes sense to examine students' expected earnings in their mid-thirties.

Another concern related to earnings expectation is how reliable this variable is in measuring students' future earnings beliefs. When asked about their expected own

[13] See the exact wording of the question in Appendix B which also provides other important survey questions.



(a) Expected Monthly Earnings (RMB)

(b) Financial Knowledge Score

(c) Monthly Allowance

(d) Monthly Allowance Balance

Figure 4: Distribution of Key Variables

earnings, survey participants were provided with information on population earnings (i.e. average monthly salary) associated with different levels of educational attainment, ranging from junior high school diplomas to postgraduate degrees. However, respondents may have formed their earnings beliefs conditional on the intention to stay on at school, the level of further education to achieve, and also the field of study to pursue. Expected earnings are likely to vary depending on all these possible choice scenarios, which we do not observe from the survey and therefore cannot model in this study.[14] Importantly, the estimation results based on the variable might therefore overstate the effect of financial literacy. To circumvent this measurement issue, for our future work it would be necessary to examine the variation in earnings expectations across differ-

[14]In particular, we do not have the information on students' expectation of their educational attainment.

ent levels and types of education, which could allow us to isolate students' schooling intentions (and career aspirations) from their earnings beliefs.[15]

3.2.2 Variables Measuring Financial Literacy

Financial knowledge is the core measure of financial literacy. In this paper, we approximate a student's financial knowledge with her understanding of basic financial concepts such as compound interest, inflation, and personal financing. More specifically, in the questionnaire three questions are designed to ask the respondent to (i) calculate compound interest, (ii) evaluate their purchase power when prices increase at the same rate as the allowance from parents, and (iii) choose appropriate ways to "make money with money." The answers to each of these three questions are scored on a 0–100 scale, and three scores are obtained: the score of compound interest, the score of inflation, and the score of financing. The average of these scores is used to measure the respondent's financial knowledge. The distribution of the scores is displayed in Figure 4b. The average score is approximately 52 points, suggesting that overall these students' financial knowledge is limited. In what follows, we use the standardized scores to measure students' financial knowledge.[16]

3.2.3 Control variables

The basic control variables are selected on the basis of three categories: personal characteristics, family background, and personal disposable income. Among the respondents, males account for 52.6 percent. Most of the respondents were in 7th and 8th grades,[17] aged 14 to 16. In addition, 16.6 percent of the respondents are the only child in the family, and left-behind children account for 17.5 percent of the sample. As for family backgrounds, the average number of years of education of the more-educated parent in the family is 7.6 years, just one year more than the six years of primary education. A student's personal disposable income mainly comes from the allowance provided by

[15] For this purpose, some existing studies, such as Delavande and Zafar (2019), shed light on our future survey design and data collection.

[16] Where standardized score is stated in this study, the mean of the score is subtracted and then the de-meaned value is divided by the standard deviation.

[17] Specifically, 43.7 percent of the students were in seventh grade, 43.29 percent in eighth grade, and 13.01 percent in ninth grade. There are fewer ninth-graders in our sample because, at the time of the survey, many of them were occupied preparing for exams.

her parents and to a great extent reflects family economic conditions. The amount of monthly allowance averages 193.25 RMB and varies considerably among students, with the maximum reaching 4,000 RMB and the minimum being 0. The balance of monthly allowance, i.e. the surplus at the end of the month, is 40.33 RMB on average and is also notably different among students, ranging from 0 to 2,025 RMB. Figures 4c and 4d show the distributions of monthly allowance and allowance balance, respectively.[18]

Students' risk attitude is also under consideration. In the survey, students were asked to indicate their choice between two options in a hypothetical situation. One is a certain reward ("earning a certain 1,000 RMB"), and the other is a risky lottery game ("flipping a coin and receiving 2,000 RMB if it comes up heads or nothing if tails"). Their answers are used to measure their risk attitude. As our data indicates, 73.06 percent of the respondents are risk-averse.

Both a student's financial literacy and her subjective evaluation of the cost and benefit of education may be influenced by their cognitive ability, which cannot be directly observed or measured. To mitigate the potential endogeneity bias caused by unobserved cognitive factors, we use students' math scores in the most recent final examination as a proxy for their cognitive ability. The countywide math tests were run in schools and graded by school teachers, at the end of the academic year when most of the sampled students were aged between 14 an 16. The average score is 68.5 out of 120 points, and we use the standardized math score in the regressions.

We also look at the perceived earnings that would make students indifferent between remaining in school and leaving school to work. Or more precisely, we asked about the minimum monthly salary that would drive them to leave school for paid work (Question (7) in Appendix B). This cost indicates the price the respondent would like to "pay" for staying in school. For simplicity, in what follows we name it as the "self-assessed cost" (of staying at school instead of working). In our sample, the average of this cost is 5,722.93 RMB. The vast majority of the respondents (31.09 percent of the sample) opt for a monthly rate of 10,000 RMB or more, while 27.46 percent of the respondents choose 3,000 RMB. Provided with a monthly rate as low as 1,000 RMB, eight percent of the respondents are still willing to drop out of school for paid work.

In addition, we account for school-level fixed effects to separate the variation in

[18]In the following empirical analyses, inverse hyperbolic sine transformations are taken for the amounts of monthly allowance and allowance balance.

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Awareness of returns to education	1,737	0.68	0.47	0	1
Expected monthly earnings (RMB)	1,737	6,873.92	5,081.33	3,000	20,000
Score of financial knowledge (100-point scale):	1,737	51.59	21.76	0	100
Score of compound interest (100-point scale)	1,737	46.09	41.18	0	100
Score of inflation (100-point scale)	1,737	43.29	49.56	0	100
Score of financing (100-point scale)	1,737	65.40	14.28	0	100
Male	1,737	0.53	0.50	0	1
Only child	1,737	0.17	0.37	0	1
Left-behind child	1,737	0.18	0.38	0	1
Higher level of parents' education (year)	1,593	7.60	3.10	0	16
Monthly allowance (RMB)	1,723	193.25	270.42	0	4,000
Monthly balance of allowance (RMB)	1,730	40.37	77.63	0	2,025
Risk attitude:					
Risk-averse (%)	1,269	73.06			
Risk-neutral (%)	167	9.61			
Risk-loving (%)	301	17.33			
Math score (120-point scale)	1,681	68.51	25.53	0	120
Self-assessed cost (RMB)	1,737	5,722.93	3,170.35	1,000	10,000
Grade 7	759	43.70			
Grade 8	752	43.29			
Grade 9	226	13.01			
School 1	364	20.96			
School 2	434	24.99			
School 3	331	19.06			
School 4	608	35.00			
Financial behavior:					
made savings recently (%)	1,221	70.29			
make budget plans every month (%)	662	38.11			
make budget plans most of the time (%)	476	27.40			
seldom make budget plans (%)	393	22.63			
never make budget plans (%)	206	11.86			

students' perception of returns to education due to the quality of education, school management styles, and local labor market conditions among others. The summary statistics of the key variables are presented in Table 1.[19]

4 Empirical Results

4.1 Financial Literacy and Awareness of Education Returns

We first examine how well an individual's financial literacy explains the variation in her awareness of returns to education, denoted by *stu_income*. It is a dummy variable that takes the value of 1 when the respondent agrees that a higher level of schooling increases earnings and 0 otherwise. We apply a binary logit model to do the estimation:

$$P(stu\_income = 1|(k\_score, Y)) = \frac{exp(\alpha_0 + \alpha \cdot k\_score + \boldsymbol{\beta} \cdot Y)}{1 + exp(\alpha_0 + \alpha \cdot k\_score + \boldsymbol{\beta} \cdot Y)}. \tag{6}$$

In equation (6), $P(stu\_income_i = 1)$ corresponds to the possibility of student i agreeing that education can increase one's earnings. *k_score* is a proxy for financial literacy, measured by the standardized score of financial knowledge as explained in Section 3.2.2, and α is the coefficient on the score of financial knowledge. Y is the matrix of control variables, and $\boldsymbol{\beta}$ is the corresponding coefficient vector. Table 2 provides the regression results from different sets of control variables, where average marginal effects are reported. School fixed effects are controlled for in specification (4).

As expected, the indicator of financial knowledge enters significantly positive in all specifications, at the 5 percent level when we account for more control variables in specifications (3) and (4). These results all support that financial knowledge is positively associated with an individual's awareness of economic returns to schooling.[20] According to specification (4), a one standard deviation rise in the score of financial knowledge, *ceteris paribus*, would result in an increase of 2.4 percentage points in the probability of agreeing that higher educational attainments are associated with higher earnings. This is equivalent to the difference in magnitude between girls and boys (2.6

[19] The last five rows in Table 1 are related to financial behavior which will be discussed in detail in Section 4.4.2.

[20] In an additional specification, to measure a student's financial literacy we use her financial knowledge score standardized with the means and variances at the school level. The regression returns results that are very similar to those in specification (4).

Table 2: Financial Literacy and Awareness of Economic Returns to Education

	(1)	(2)	(3)	(4)
Standardized *k_score*	0.035***	0.026**	0.024**	0.024**
	(0.011)	(0.011)	(0.012)	(0.012)
Male		-0.027	-0.024	-0.026
		(0.023)	(0.024)	(0.024)
Standardized math score		0.038***	0.034***	0.033***
		(0.011)	(0.012)	(0.012)
Left-behind child		-0.084***	-0.077**	-0.067**
		(0.028)	(0.030)	(0.031)
Only child		-0.008	-0.025	-0.027
		(0.030)	(0.032)	(0.032)
Parents' educational attainment			0.000	0.001
			(0.004)	(0.004)
Monthly allowance, *asinh*			0.004	0.005
			(0.008)	(0.008)
Monthly balance of allowance, *asinh*			0.010	0.008
			(0.007)	(0.007)
Risk-neutral				0.004
				(0.042)
Risk-loving				-0.016
				(0.031)
Grade 8				0.036
				(0.025)
Grade 9				-0.002
				(0.040)
School fixed effects	N	N	N	Y
Observations	1,737	1,680	1,536	1,536

Notes:

Average marginal effects are reported.

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Financial knowledge score (*k_score*) and math score are standard scores.

asinh is the inverse hyperbolic sine transformation.

percentage points) but just about three quarters of the marginal effect of math score (3.3 percentage points). By comparison, the marginal effect of financial knowledge score - on the base of 68 percent - does not seem to be economically large.

Students with higher math scores, who we assume have the higher cognitive ability, are significantly more likely to agree that education increases future earnings (by 3.3 percentage points at the significance level of 1 percent). This suggests that students' higher cognitive ability may help them better understand human capital accumulation and returns to education. A primary concern related to math score is that multicollinearity may occur if it is highly correlated with financial knowledge score. If that's the case, math ability is likely to pick up the impact of financial literacy on students' perceptions of returns to schooling - not only the outcome of 'education increases income' discussed here, but also their expected earnings to be next analyzed in Section 4.2. Take the financial knowledge about compound interest, for example - to a certain extent it may reflect a student's math skills. This could be problematic because, as will be shown in Table 5 in Section 4.4.1 (which is a robustness check for the baseline estimations), compound interest knowledge appears to be one of the most important elements in explaining the variance in perceptions of returns to education.

However, on closer examination we posit that this is not a worrisome issue. First, in the math curriculum the concept of compound interest is not introduced until high school, which is especially the case in poor rural areas. Second, our data indicates only weak or negligible correlations between math score and average financial knowledge score (0.1358) as well as detailed score of compound interest (0.0714). Third, Table 5 reveals that knowledge about financial investment, another component of measured financial knowledge which is less related to math skills, is strongly correlated with students' awareness of educational returns. In fact, the average marginal effect of investment knowledge on the awareness of economic returns to schooling triples in size compared with that of compound interest knowledge, with the coefficient statistically significant at 1 percent. Therefore, there is some reassurance that the financial knowledge score, especially the score of compound interest, is not picking up one's math ability.

Besides, compared with non-left-behind children, left-behind children are less likely to agree on the benefits of education. The finding is consistent with the evidence provided by McKenzie and Rapoport (2011) and Zhou et al. (2014), who suggest that parental absence may translate into youths' lower schooling attendance and attainment.

All other variables do not appear to be significantly correlated with the outcome variable. Notably, parents' educational attainment does not seem to have a significant impact on students' awareness of returns to schooling and the effect is negligible in magnitude. In general, parents' educational levels positively affect teenagers' attitudes to education and educational aspirations. However, as Coleman (1988) points out, such a positive influence is usually associated with a benign parent-child relationship acting as an "incubator." In fact, while teenagers develop their beliefs about parental authority to impose rules and restrictions, they are prone to exhibit "psychological reactance" and defying their parents (Donnell et al., 2001; Van Petegem et al., 2015). Whereas parents with higher levels of education are more likely to advocate the importance of schooling because of their higher expectations for their children (Davis-Keen, 2005; Wang et al. 2016). As a result, their children could sometimes have negative attitudes towards school, resulting in an insignificant correlation between parents' educational levels and teenagers' awareness of educational returns.

4.2 Financial Literacy and Expected Monthly Earnings

We propose the following multivariable linear regression model to examine the impact of students' financial literacy on their expected monthly salaries in 20 years:

$$wage\_expect = \theta_0 + \theta_1 \cdot k\_score + \boldsymbol{\beta} \cdot X + \varepsilon, \tag{7}$$

where *wage_expect* is the natural logarithm of expected future earnings. In the survey, we asked students about their expected monthly earnings by offering six choices of income levels ranging from "less than 3,000 RMB" to "more than 20,000 RMB." The data is illustrated in Figure 4a. To account for right-censoring in the dependent variable, we apply a Tobit model to examine the correlation between financial knowledge and expected monthly salaries.

Table 3 presents the Tobit regression results with different sets of control variables. School fixed effects are controlled for in specifications (4) and (5).[21] In the latter, we

[21] We also estimate a model with the same set of control variables as in specification (4) but with the financial knowledge score standardized at the school level. The estimation results are broadly comparable to those in specification (4).

Table 3: Financial Literacy and Expected Monthly Earnings

	(1)	(2)	(3)	(4)	(5)
Standardized *k_score*	0.07***	0.05***	0.06***	0.05***	0.05***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.018)
Male		0.15***	0.14***	0.14***	0.14***
		(0.036)	(0.038)	(0.037)	(0.036)
Standardized math score		0.18***	0.16***	0.16***	0.13***
		(0.018)	(0.019)	(0.019)	(0.018)
Left-behind child		-0.06	-0.04	-0.05	-0.05
		(0.046)	(0.049)	(0.050)	(0.048)
Only child		-0.04	-0.05	-0.06	-0.05
		(0.048)	(0.050)	(0.050)	(0.048)
Parents' educational attainment			0.02***	0.03***	0.02***
			(0.006)	(0.006)	(0.006)
Monthly allowance, *asinh*			-0.01	-0.01	-0.01
			(0.013)	(0.014)	(0.013)
Monthly balance of allowance, *asinh*			0.01	0.01	0.01
			(0.011)	(0.011)	(0.010)
Risk-neutral				0.08	0.11*
				(0.066)	(0.063)
Risk-loving				0.12**	0.11**
				(0.049)	(0.047)
Grade 8				0.14***	0.08**
				(0.040)	(0.038)
Grade 9				0.16***	0.12**
				(0.061)	(0.059)
Self-assessed opportunity cost					0.06***
					(0.006)
Constant	8.62***	8.56***	8.42***	8.21***	7.91***
	(0.018)	(0.028)	(0.086)	(0.102)	(0.101)
School fixed effects	N	N	N	Y	Y
Observations	1,737	1,680	1,536	1,536	1,536

Notes:
Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.
Financial knowledge score (*k_score*) and math score are standardized scores.
asinh is the inverse hyperbolic sine transformation.

also include the self-assessed cost of remaining in school, namely the threshold salary that could drive the student to quit school for a paid job, as described in Section 3.2.3.

As Table 3 indicates, the effects of financial knowledge are significantly positive at the 1 percent level in all five specifications, strongly indicating that expected future earnings increase with the level of financial knowledge. Precisely, a one standard deviation increase in the financial knowledge score, *ceteris paribus*, would result in the expected earnings rising by 5 to 6 percent as indicated in specifications (3) - (5). This finding supports our theoretical model in Section 2 which states that students with higher financial literacy generally expect higher returns to education. It is worth noting that the magnitude of this impact is smaller than the estimated economic returns to cognitive abilities in existing studies, especially for developing countries. As reviewed by Hanushek and Woessmann (2008), the proportional rise in individual wages, as a result of a one standard deviation increase in cognitive skills scores, ranges from 5% to 48% in developing countries. Although these figures are not directly comparable with our results in terms of variable definitions and estimation techniques, the relatively small size of the marginal effects of financial knowledge, in both Logit and Tobit models, implies that there may be some attenuation bias in these estimations. We will further discuss this matter in Section 4.3.

Further, a positive marginal effect of financial knowledge score on expected earnings could reflect that, with sufficient financial literacy, an individual is more inclined to invest in education and agree education increases earnings. Whereas as Table 2 in the previous section shows, financial literacy has a relatively limited impact on a student's awareness of economic returns to education. Therefore, the positive effect on earnings expectation to a greater extent could be driven by the correlation between financial literacy and expected educational investment. In other words, those who are more financially literate might intend to continue education and also expect higher future earnings. On the other hand, as pointed out earlier in Section 3.2.1, the information on expected earnings was collected without conditioning on students' intentions to stay on at school, or go to further education. As such, the impact of this intention on earnings expectation might be picked up by the financial literacy variable. This will lead to a relatively larger and robust effect of financial knowledge on expected earnings, as compared with its effect on the awareness of educational benefits.

Interestingly, the findings from the previous section suggest that left-behind children tend to undervalue educational benefits, compared to their counterpart peers who live with parents. Specifically, being a left-behind child lowers the likelihood to approve of earnings advantages of education, by 6.7 percentage points at the significance level of 5 percent. By contrast, when it comes to expectations of future earnings, the negative effect of being a left-behind child loses significance, and the estimated coefficients become smaller in magnitude.

The different estimates could arise from different mechanisms for parental migration to influence a child's perceptions of educational returns. Indeed, a secure relationship with parents lays a positive foundation for the child's personality and long-term physical and psychological well-being. Thus the lack of parental attention or supervision is usually associated with children's less interest in education. This results in lower intentions to pursue further education, which translates into lower expected earnings in our context. This adverse impact, however, can be obscured by the positive effect from parental migration. In most cases, parents leave home to work in urban areas for higher paid jobs so as to ease family economic burdens. In spite of parental absence, left-behind children receive remittances from their parents and also benefit from the overall improved household welfare. When asked about their expected earnings in twenty years' time, they may have based their beliefs on their parents' current income, which is in general higher than the average local labor market outcomes. Besides, parental migration could also positively influence children's educational and occupational aspirations if they were to migrate to join their parents in the urban areas, for better education in the short run as well as more promising employment prospects in the future (e.g., Wang, 2014). As a result, they may expect higher earnings. Therefore, although parental absence might play a dominant role in adversely affecting a child's expected earnings, this negative impact can be partly offset by the positive influences from parental migration. This leads to the overall negative coefficients which are relatively small in size and statistically insignificant.

In addition, our results suggest a significantly positive influence from parents' educational attainment, in contrast to its insignificant and negligible impact on their children's awareness of economic returns to schooling as suggested in Section 4.1. This implies that, although teenagers tend to disagree with their parents in terms of the value judgment of education benefits, they may subconsciously refer to their parents' income level when evaluating their own expected earnings.

Students in higher grades and students with better academic records - measured by the most recent math score - seem to expect higher future earnings. So do male students, compared with their female counterparts. It could be that students may also base their earnings expectation on the wages observed from the local labor market where, overall, women earn less than men.

Compared with risk-averse students, risk-seeking students appear to expect higher earnings and this difference is mostly statistically significant. Indeed, human capital investment is usually associated with risks, i.e. intrinsic uncertainties in achieving expected economic returns (Carneiro et al., 2003; Belzil and Leonardi, 2007; Glocker and Storck, 2014). In this sense, risk-seeking students are more willing to embrace uncertainty when making their schooling decisions, in hopes of obtaining higher pecuniary payoffs.

Another variable in question is a student's self-assessed cost of remaining in school (instead of leaving school for paid work). Intuitively, the more the student perceives this cost, the higher she values the investment in schooling, leading to higher expectations about earnings. This is confirmed by the estimation results in column (5). Finally, neither the monthly allowance nor the balance of monthly allowance appears to be significantly correlated with one's expected monthly salary, consistent with what is found in Table 2.

4.3 Potential Endogeneity Problem

Tables 2 and 3 include various variables such as students' financial status, personal characteristics, and parents' educational attainment. School fixed effects are also controlled for. Additionally, we measure a student's cognitive ability with her math score from the most recent final exam. However, it is important to keep in mind that using test scores to control for cognitive ability is subject to potential endogeneity issues.

A problem inherent in test scores relates to the measurement technology. Test scores could vary with test taking conditions even with the same set of exam questions. Besides, the scope and content of the exams *per se* could be dubious when it comes to the reliability of the questions in measuring cognitive ability. One concern is that the exam questions are generally not adequate to cover all aspects of knowledge with regard to cognitive capacities. Specifically, the math score used in this paper is only one dimension to approximate these abilities, while there are a wide range of other performances to be considered, such as verbal skills, general science, and memory. Nonetheless, existing evidence indicates that test scores from these different subjects tend to be highly correlated (Hanushek and Woessmann, 2008) and that math test scores are relatively more important in explaining the impact of cognitive abilities (e.g., Agarwal and Mazumder, 2013). These findings are reassuring in that, as far as measurement errors are concerned, math scores could be a well-established proxy for students' cognitive traits in question.

A more important endogeneity issue lies in omitted variables, which on the one hand can be associated with a student's perception of educational benefits, and on the other hand may affect her math scores as well as her financial knowledge scores. Unmeasured factors, such as family's socio-economic status, could result in endogeneity bias due to the correlation between the error term and the explanatory variables. Similarly, unobserved noncognitive abilities - including personality traits, mindset, and social skills (Heckman et al., 2006) - might also play an important role in this matter.

Of particular concern in our study is students' family background, as it may be correlated with an important component of financial literacy, knowledge about compound interest rates. The understanding of compound interest may reflect a student's family background (or more specifically, parents' experience of investment and savings), rather than just directly influence her expectation of returns to schooling. However, this is not worrying in the particular context of this paper, where more than forty percent of the county's low-wage population migrate to urban areas for higher paid jobs, leaving their children behind. Arguably, very few families in the sample are likely to be experienced in investment or familiar with financial knowledge. In fact, as reflected by sample characteristics, parents' levels of educational attainment average 7.6 years, just exceeding the six years of primary education. Besides, most of the survey participants were boarding students, and nearly one-fifth of the students were left-behind children, indicating very little parental tutoring and thus negligible influences from family on students' financial literacy. For similar reasons, it is sensible to expect that family background bears little influence on students' cognitive abilities such as math skills.

Still, other important factors, especially non-cognitive traits such as study motivation, are not observed in the data and thus are not controlled for in the models. If these omitted variables are correlated with the model's explanatory variables and also pick up students' perceptions of educational benefits, our baseline estimations can be prone to endogeneity bias. Therefore, we proceed to perform instrumental variable (IV henceforth) estimations, using controls that can be observed, in an attempt to mitigate the endogeneity bias.

Drawing upon previous studies on peer effects by Angrist (2014) and von Hinke et al. (2019), this paper instruments a student's financial knowledge using the class-level group average score of financial knowledge. An individual student's financial knowledge can be influenced by her fellow classmates through peer effects. Meanwhile, the schools in our sample do not provide students with school-based financial-education programs, therefore there does not exist an unobserved class-level heterogeneity that is correlated with the student's financial knowledge and in turn, her perception of returns to schooling. In this sense, the average financial knowledge score on class level is relevant in explaining the variations in a student's perceptions of education returns and expectations for future earnings, but only conditional on the financial knowledge of the student in question. As such, the IV satisfies both the relevance and exclusion restrictions (Gormley and Matsa, 2014).

Table 4 reports the IV regression results. The statistically significant coefficient in column (1) confirms that the IV is a strong predictor of financial knowledge: the class average score of financial knowledge is positively correlated with an individual's financial knowledge at the significance level of 1 percent. Columns (2) to (5) present the IV estimation results, among which column (3) reports the average marginal effect. Also included in the table are the results from underidentification test, F test for weak instruments, and Wald test for exogeneity of the instrument, all suggesting that the instrument is valid. Importantly, the coefficients of financial knowledge are all statistically significant and positive, consistent with the results discussed earlier from Logit model and Tobit model. Specifically, an increase in financial knowledge score by a one standard deviation translates into an increase in the likelihood to agree on educational returns by 14 percentage points, as well as an increase in expected earnings by 28 percent. Both effects are statistically significant at the 1 percent level, strongly supporting our previous findings that an individual's financial knowledge can help improve her perceptions of economic returns to schooling.

Table 4: Instrumental Variable Regressions

	Standardized *k_score*	Awareness of returns to education		Expected monthly earnings	
	(1)	(2)	(3)	(4)	(5)
	1st stage OLS	2SLS	IV Probit	2SLS	IV Tobit
IV: Class average *k_score*	0.047***				
	(0.006)				
Standardized *k_score*		0.152**	0.140***	0.198***	0.280***
		(0.063)	(0.045)	(0.071)	(0.096)
Observations	1,536	1,536	1,536	1,536	1,536
p value for underidentification test		0.000		0.000	
F-statistic for weak IV		61.022		60.334	
Wald test statistic of exogeneity			4.89		6.17
p value for Wald test of exogeneity			0.027		0.013

Notes:
Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.
Control variables are the same as in specification (4) in Tables 2 and 3.
Average marginal effect of Standardized *k_score* is reported in column (3).
Underidentification test gives a p value of zero, implying that the instrument is relevant.
F-statistic for weak IV is greater than critical value (16.38), indicating no presence of a weak instrument.
Walt test statistic is significant, therefore the null hypothesis that the IV is exogenous cannot be rejected.

Moreover, the IV estimates are greater than the baseline estimates reported in Tables 2 and 3 where the corresponding coefficients are 0.022 in Logit model and 0.04 in Tobit model respectively. This finding is consistent with the evidence provided in the aforementioned Angrist (2014)'s study that IV estimates exceed the corresponding OLS estimates. In fact, the same patterns are commonly observed in the literature on returns to schooling, as reviewed by Card (2001).

There can be several probable reasons that explain the divergence between the conventional estimates and IV estimates. First, as Ashenfelter and Krueger (1994) point out, unobserved family-related factors do not necessarily lead to upward bias in the OLS estimates of returns to schooling. On the other hand, even if omitted variables such as ability and family background do cause upward bias in our baseline estimates, this overestimation can still be offset by other unobserved factors that are negatively correlated with financial literacy, such as some unmeasured financial attitude, which could possibly lead to a considerable downward bias instead. Second, similar to the scores of cognitive tests, financial knowledge scores may also be measured with random errors, perhaps due to some "group-specific variance components" in the variable (Angrist, 2014). This measurement error can bias the OLS estimate toward zero. Whereas the IV estimation takes account of this endogeneity using the class-level average score of financial knowledge, thus the IV estimates are unaffected by the measurement error and could be larger than the OLS estimates. Third, it may also be that while the OLS estimate describes the average treatment effect (ATE) over the entire population, IV is estimating the *local* ATE (LATE) of improving financial literacy only for individuals who are affected by the instrument, namely the average financial knowledge score on the class level. This could also yield larger IV estimates, compared with OLS estimates (Imbens and Angrist, 1994). For all these reasons, there is a wedge between OLS and IV estimates. And considering the potential bias in the preceding Logit and Tobit estimates, the IV estimations provide an important tool to control for the endogeneity and thus may help alleviate the attenuation bias.

4.4 Further Discussions on Financial Literacy

We conduct additional regressions to establish the robustness of the results presented in Tables 2 and 3. First, the financial knowledge score is broken down to detailed financial scores; then we add variables related to financial decisions to the regressions. The positive correlations found in the previous sections prove robust to a number of alternative specifications.

4.4.1 Detailed Financial Knowledge

As discussed in Section 3.2.2, the financial knowledge score is an average of a student's knowledge about compound interest, inflation, and financial investment. In this section, we further investigate the impact of each of these scores, which are standardized for the convenience of comparison.

Columns (1) and (2) in Table 5 present the new regression results. The score of compound interest is positively correlated with both of the outcome variables, meaning that students with better understanding of compound interest are significantly more likely to agree that education increases personal income and expect higher future earnings. On the other hand, no significant correlation exists between a student's knowledge about inflation and the outcome variables. Students' understanding of financial investment does not seem to explain the variance in their expected future labor market payoff either.

Table 5: Regressions on Detailed Financial Knowledge or Financial Behavior

	(1)	(2)	(3)	(4)
	Education increases income	Expected future income	Education increases income	Expected future income
	Logit	Tobit	Logit	Tobit
Standardized score of compound interest	0.021*	0.057***		
	(0.012)	(0.018)		
Standardized score of inflation	-0.006	0.011		
	(0.012)	(0.018)		
Standardized score of financial investment	0.064***	0.020		
	(0.012)	(0.018)		
Standardized *k_score*			0.024*	0.049***
			(0.012)	(0.018)
Frequency of budget planning			0.007	-0.020
			(0.012)	(0.019)
Made savings recently			0.013	-0.014
			(0.030)	(0.046)
School fixed effects	Y	Y	Y	Y
Observations	1,536	1,536	1,536	1,536

Notes:
Average marginal effects are reported for logit models.
Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.
Control variables are the same as in specification (4) in Tables 2 and 3.
Financial knowledge score (*k_score*), detailed financial knowledge scores, and math score are all standardized.
asinh is the inverse hyperbolic sine transformation.

These findings are in line with what our theoretical model predicts. Indeed, compound interest is a typical example of non-linearity, as it involves the nonlinear relationship between the interest rate and the amount of money accumulated at the end of a period. It relates to a special case of the ironing heuristic, namely the exponential growth bias in financial decision-making as discussed in Section 2.2. Students with insufficient financial knowledge particularly in compound interest are more likely to evaluate the complicated non-linear payoff schedules by simply linearizing it. This heuristic bias would drive them to perceive the average payoff to their study efforts as the marginal payoff at the convex phase of human capital formation, resulting in an underestimation of returns to education. Whereas the other two aspects of financial knowledge, i.e. the understanding of inflation and financial investment, are in fact less relevant in the context of the non-linear relationship. As such, students who are financially illiterate in terms of these two aspects are less affected by the ironing heuristic, at least in terms of their expectation of future earnings. In light of these findings, we expect that different aspects of financial knowledge could have different effects on a student's perception of returns to education. This provides a policy implication that informational interventions should distinguish behavioral biases that are caused by different aspects of financial illiteracy.

4.4.2 Financial Behavior

Although financial knowledge is the core of financial literacy, it does not cover the whole story. In addition to the understanding of financial concepts and risks, financial literacy also involves the skills, motivation, and self-efficacy to apply such knowledge to make effective decisions in various financial contexts (OECD, 2017). Therefore we also need to consider financial behavior which is an essential element of financial literacy. It involves the actions a student does or does not take in a specific situation to secure her financial future. Specifically, we examine the financial behavior from two aspects: how often she makes budget plans and whether she made savings recently. According to the descriptive statistics shown in Table 1, 70.29 percent of the respondents made savings recently; 38.11 percent of respondents make budget plans each month, while 11.86 never make budget plans.

We include these financial behaviors in our model. Regression results of specifications (3) and (4) in Table 5 provide evidence that planning and saving behaviors have no significant correlation with students' awareness of returns to education or their expected future earnings. Meanwhile, the indicator of financial knowledge remains significantly positive in both specifications, and the coefficients are comparable with our previous findings. In brief, our empirical findings in Tables 2 and 3 hold in various robustness checks.

5 Conclusions and Policy Discussion

In an attempt to encourage participation in compulsory education, governments around the world have provided rural schools and low-income families with educational subsidies. These policies intend to motivate financially needy students to attend school by easing the financial burden on them. However, rural teenagers' willingness to study remains a challenge: the opinion of "schooling is useless" prevails widely in some regions and countries, and the dropout rates in many rural secondary schools remain high.

This paper investigates the factors influencing rural students' perception of returns to education from the perspective of financial literacy. In a two-period model of human capital investment, we examine the association between insufficient study efforts and the misperception of returns to education due to poor financial literacy. The theoretical analysis shows how the ironing heuristic causes a financially illiterate student to deviate from the optimal level of study efforts. Due to ironing heuristics, financially illiterate students tend to underestimate the marginal effect of human capital investment on their future earnings, resulting in suboptimal educational investments.

Using survey data from four rural junior high schools in Southwest China, we provide empirical evidence of significantly positive impacts of one's financial literacy on her perception of returns to education. Moreover, students with poor knowledge about compound interest are found to perceive lower returns to education, which is in line with our theoretical assumption that poor financial literacy is associated with linearization bias and an underestimation of returns to schooling.

These results are most applicable to poor areas in developing countries with similar settings as outlined in the model, where the access to credit markets is limited for financing education (Banerjee and Duflo, 2012) and marginal costs of study effort are particularly high (because of living in poverty-stricken areas, having little parental support, needing to help parents especially during farming season, etc.). Whereas the external validity remains unclear in other contexts, especially for more developed regions within the country or other developed countries. Thus, future research is needed to further examine the impact of financial literacy by extrapolating the study to other populations.

While the evidence provided by the paper mainly pertains to the population in poor rural areas, our study clearly delivers two insights into more effective interventions in information in a more general background. Our empirical analysis suggests that parental educational attainment is significantly positively correlated with students' earnings expectations. The underlying reason could be that more educated parents are more likely to be aware of economic returns to schooling. As such, an impactful way of disseminating information about educational benefits can be through parents.

More importantly, the traditional informational intervention has been limited to information about educational costs and benefits, without considering whether students understand the information before they make schooling decisions. Given that students' financial literacy is influential in shaping their understanding of returns to education, it is necessary to provide them with learning programs with great emphasis on financial knowledge, especially knowledge of non-linearity such as compound interest calculation. By helping them better understand the nonlinear characteristics of human capital accumulation, such financial education programs can contribute to reducing their "ironing" heuristic cognitive bias.

This kind of financial education programs are particularly important for rural students in poor regions, especially those left-behind children who, as our findings indicate, tend to underevaluate the economic returns to education. In addition, since there is little demand for financial service among rural students, they can hardly foresee any benefit from learning financial knowledge. Therefore, it is crucial to design other financial education curricula to improve these students' noncognitive abilities in terms of goal setting, self-control, delayed gratification, etc. In the short run, rural students will derive much benefit from these programs which, in the long run, can motivate them to devote more efforts to schooling.

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Appendix A Junior High School Key Statistics (2017)

	M County	Autonomous Prefecture	China
Gross Enrollment Ratio (%)	99.5	113.3	103.5
Graduation Rate (%)	86.7	90.3	98.7
Promotion Ratio of Graduates (%)	86.1	88.2	94.9

Notes:

The World Bank defines gross enrollment ratio as the ratio of total enrollment in junior high schools, "regardless of age, to the population of the age group that officially corresponds to the level of education" (junior secondary education in this study).

Promotion ratio of graduates is the percentage of junior high school graduates who are promoted to senior secondary education in the next academic year.

Main sources:

Yearbook of Prefecture (2018)

Educational Statistics Yearbook of China (2018)

Appendix B Selected Questions in the Questionnaire

(1) *Awareness of returns to schooling*

Which of the following statement(s) do you agree on? (Select all that apply.)

A. The higher one's educational attainment is, the higher the future earnings.

B. My parents do not earn much; I will probably be like that in the future.

C. Growing up poor, I still believe that I can improve my family's financial situation as long as I work hard.

D. None of the above.

(2) *Expected earnings*

How much do you think you could earn per month in twenty years? For your reference, here is the average salary by education level: 2,000 RMB for junior high school graduates, 3,000 RMB for high school graduates with a high school diploma, 4,000 RMB for those with a two- or three-year college diploma, 5,000 RMB for college graduates with a bachelor's degree, 8,000 RMB for those with higher qualifications (such as a master's degree, a doctorate degree, or a professional degree).

A. 3,000 RMB or less

B. 4,000 RMB

C. 5,000 RMB

D. 6,000 RMB

E. 7,000 RMB

F. 10,000 RMB

G. 20,000 RMB or more

(3) *knowledge about compound interest*

Suppose you put 1,000 RMB into a savings account that compounds annually at an interest rate of 5%. At the end of the second year, how much interest would you have earned?

A. Do not know

B. Less than 100 RMB

C. 100 RMB

D. More than 100 RMB

(Grade points are assigned as follows: A=0, B=50, C=70, and D=100.)

(4) *knowledge about inflation*

If the retail prices at school rise by 10%. Meanwhile, the monthly allowance from your parents also increases by 10%. How would you feel about this change in your situation?

A. Getting better

B. Getting worse

C. No difference

(Grade points are assigned as follows: A=0, B=0, and C=100.)

(5) *knowledge about personal financial investment*

In your opinion, which of the following is (are) the desired way(s) to "make money with money?" (Select all that apply.)

A. Bank savings

B. Stock investment

C. Investment with personal finance apps

D. Buying lottery or gambling

E. Usury

F. None of the above

(Grade points are assigned as follows:
A=20 (or 0 if not choosing A),
B=20 (or 0 if not choosing B),
C=20 (or 0 if not choosing C),
D=0 (or 20 if not choosing D),
E=0 (or 20 if not choosing E), and
F=0.)

(6) *Risk attitude*

Consider the hypothetical situation where you are provided with two options: (i) a certain reward ("earning a certain 1,000 RMB") and (ii) a risky lottery game ("flipping a coin and receiving 2,000 RMB if it comes up heads or nothing if tails"). Which option would you prefer?

A. A certain reward of 1,000 RMB

B. A risky lottery game with the reward of 2,000 RMB or nothing

C. No difference between A and B

(7) *Self-assessed cost of staying at school*

Consider the hypothetical situation where you are offered a *full-time* paid job. In this situation, you would like to quit school for this job if you are paid a minimum monthly salary of:

A. 1,000 RMB or less

B. 3,000 RMB

C. 4,000 RMB

D. 5,000 RMB

E. 7,000 RMB

F. 10,000 RMB or more

From Grants to Loans and Fees: The Demand for Post-compulsory Education in England and Wales from 1955 to 2018*

(Joint with Peter Dolton)

Abstract

The UK has progressively moved from a Higher Education (HE) system which is primarily funded at the taxpayers' expense to one with individual participants (and their parents) paying a larger share of the education cost by scrapping student grants, introducing student loans, and charging tuition fees. This paper investigates the impact of these changes on the demand for HE using time-series data for England and Wales over the period from 1955 to 2018. In a Seemingly Unrelated Regressions framework, we model young people's three-stage schooling decisions, allowing for structural breaks. Tests show that most of the breaks occurred in line with several important policy changes, and there existed gender differences in the break points. Estimation results suggest that net college cost has had a significantly negative but quantitatively small impact on university entrance. In examining the net liquidity available to HE students during their studies, we find that the demand for HE appears insensitive to changes in students' net liquidity over the post-1998 era. Moreover, the impacts of net college cost and net liquidity both vary by gender.

Key words: Post-compulsory education; HE finance; Structural change

JEL: I22, I28, J08

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1 Introduction

The past few decades have witnessed substantial expansions of the higher education (HE) sector in numerous countries throughout the world. For instance, across the Organization for Economic Co-Operation and Development (OECD) countries, the average tertiary attainment rate has increased by 21 percentage points since 2000, reaching 48 percent in 2021 (OECD, 2022). This radical expansion of HE, however, has put a heavy financial strain on public HE funding in some countries. Consequently, it could be difficult to provide free HE without impairing either access to HE or the quality of HE (Barr, 2004). This necessitates changes in HE finance arrangements. With increasingly tight budgets in the HE sector, tuition fees are called in to shift more of the responsibilities for paying education costs from taxpayers to students (and their families). Such a move in many cases is facilitated by loan-based aid, which governments offer students in an attempt to ease the extra financial burden that the new system places on them.

The prevalence of fees and loans has been accompanied by the scrapping of traditional need-based grants. Although it has been long established that student grants can lower the cost of post-compulsory education, the evidence of their effect on college enrollment has been mixed. Relatively sizable positive impacts are found in France (Fack and Grenet, 2015), the US (Dynarski, 2003; Kane, 2007), and the UK (Dearden et al., 2014), whereas the evidence from Denmark (Nielsen et al., 2010) and Germany (Steiner and Wrohlich, 2012) suggests positive but quantitatively smaller effects on enrollment. Furthermore, according to Carruthers and Welch (2019), almost no influence on college enrollment is found for one of the largest federal grant programs in the US, the Pell Grant.[1]

In contrast to grants, student loans do not reduce individuals' education costs directly but instead postpone payment for the costs. Moreover, student loans are accessible to a broader range of students. For policymakers, student loans serve as a useful policy tool to relieve the financial pressure on public funding. For individuals, fee loans provide a way to alleviate their credit constraints when they are liable for tuition fees. In particular, the repayment scheme of income-contingent loan systems - operating in countries such as Australia, Canada, New Zealand, and the UK - allows HE students to

[1]Dynarski et al. (2022) provide an extensive review of the literature on financial aid, including the traditional need-based grants.

defer their tuition fees until after graduating, only if their income reaches a repayment threshold.

Despite these advantages of student loans over alternative forms of student aid, debt-averse students may still be reluctant to take up loans to pursue HE (e.g., Field, 2009). Besides, in contrast to income-contingent loans, mortgage-style loans in the US require that graduates make fixed monthly repayments over a fixed period of time, irrespective of their income level. This system has been questioned, particularly in that it imposes a heavier economic burden on low-income graduates (Barr et al., 2019). Moreover, student loans can be subject to delinquency and default risks, especially when students and graduates are faced with uncertain labor market conditions. Take the federal student loans in the US, for example - after staying stable for nearly a decade, the default rates on the loans increased dramatically following the financial crisis of 2007–08 and the Great Recession (Lochner and Monge-Naranjo, 2016). On the other hand, in England, the loan repayment period is set at 30 years under the current loan repayment scheme of income-contingent system, meaning that any outstanding debt will be written off 30 years after graduates first make their repayment. As projected in a study by Crawford and Jin (2014), only 27 percent of the graduates will be able to repay all their student loans within the repayment period. What's more, the average amount written off could be remarkably high, which is estimated to be £30,000.

Given the multifaceted feature of student financial aid, the funding reforms have been the subject of ongoing debate. In fact, the switch from a free college scheme towards an HE system featuring high tuition fees coupled with high student loans is more notable in the UK than in other countries lately. Over the past few decades, there has been a seismic change in the university system in the UK. With successive reforms, it has progressively moved from a free college system which is primarily funded at the taxpayers' expense to one where individual participants (and their parents) pay a larger share of the costs of their education by scrapping student grants, introducing student loans, and charging tuition fees. Furthermore, these HE finance reforms have been accompanied by a sequence of other HE policy changes.

All these changes might have caused a structural shift in the way universities operate. More critically, although it was argued that changes in funding arrangements would provide policymakers leverage to widen participation, there has been increased concern that the rise in fees could have reversed the rising trend of HE participation. This raises the key question that this paper aims to address: what is the impact of these policy changes on the demand for HE? This question is crucial in that the future shape of the UK university system will depend on the nature of this reaction.

These issues have already drawn growing attention in the existing literature. Related cross-sectional studies by Sá (2019) and Azmat and Simion (2021) suggest that the recent HE funding reforms have negative effects on HE participation although the magnitude of the effects is small. Using combined data that covers a longer time period, Murphy et al. (2019) investigate the holistic effect of a set of funding reforms over the past decades. The authors demonstrate that overall university enrollment continued to rise over the post-reform era, while the socio-economic gap in participation remains stable. They also examine the net liquidity that's available to college students during their university studies. By comparing this net liquidity with two forms of living cost, they suggest that the increasing net liquidity is not enough to cover the cost. To our knowledge, little rigorous time-series research has been devoted to this topic. Our paper aims to fill this gap by providing time-series evidence on the demand for post-compulsory education in England and Wales, over the time period from 1955 to 2018 which saw great variation in HE policy. In our analysis, we focus on the causal effects of net college cost as well as the aforementioned net liquidity on HE participation.

The main outcome of interest in this paper is the demand for post-compulsory education. More specifically, we examine young people's sequential decisions to stay on at school past the compulsory minimum school leaving age. In fact, most pupils who do not enter training or try to enter the labor market at the age of 16 will stay on in schools or colleges of further education, before they take the 'A' level examinations at the age of 18.[2] Those who pass two or more 'A' levels will be qualified to enter university in the same year.[3] Accordingly, we define: (i) the post-16 staying on rate as the proportion

[2]The school leaving age in England and Wales was set at 15 in 1947 and was raised to 16 in September 1972. In England, the school leaving age was further raised to 17 in 2013, and, most recently, was extended to 18 in 2015. English students nowadays must stay in school until the age of 16, and are then required to remain in full-time education or take on vocational training or apprenticeship until the age of 18. In order to make the data comparable over the entire period under study, for school leavers in most recent years we will still focus on those aged 16.

[3]Nowadays the standard requirement for undergraduate courses in the UK is three 'A' levels. There are also alternatives to 'A' levels: students can enter universities with qualifications such as Access to Higher Education Diplomas and vocational qualifications. However, to maintain consistency in the

of the 16-year-old age group attending schools and colleges of further education; (ii) the qualified leaver rate as those qualified leavers with two or more 'A' level passes as a proportion of the relevant age group; and (iii) the university entrance rate as the university entrants as a percentage of the relevant age group. These variables are defined on the basis of Pissarides (1982)'s work on post-compulsory education, which will be discussed in more detail in Section 3.2.

Apparently, the relations between these three rates are logically interconnected and ordered recursively in that the staying on rate will inevitably change the qualified leaver rate, and that the university entrance rate can only rise if both these two have risen. Therefore, it is important to study these decisions together and model them in a sequential way: to stay on at school past the compulsory minimum school leaving age, to qualify for university entrance after two years, and to enter university in the same year.[4]

It should be noted that the university entrance rate here is defined as new entrants to first-degree undergraduate courses in universities and colleges as a percentage of the 18-year-old age group. The definition is not based on the standard ones that are commonly used in official statistics. As such, it is lower than the official participation indices such as the Age Participation Index (API) and the Higher Education Initial Participation Rate (HEIPR). In the data section (Section 4), we will provide a detailed comparison of these measures.

Figure 1 depicts the trends in these rates over the past six decades.[5] Evidently, the staying on rate, after the increase of school leaving age in 1972 is controlled for,[6] has been rising steadily over the whole period, especially in the 1980s and 1990s when there was a substantial increase in the proportion of 16-year-olds remaining in school. Clear upward trends can also be seen in the qualified leaver rate and the university entrance

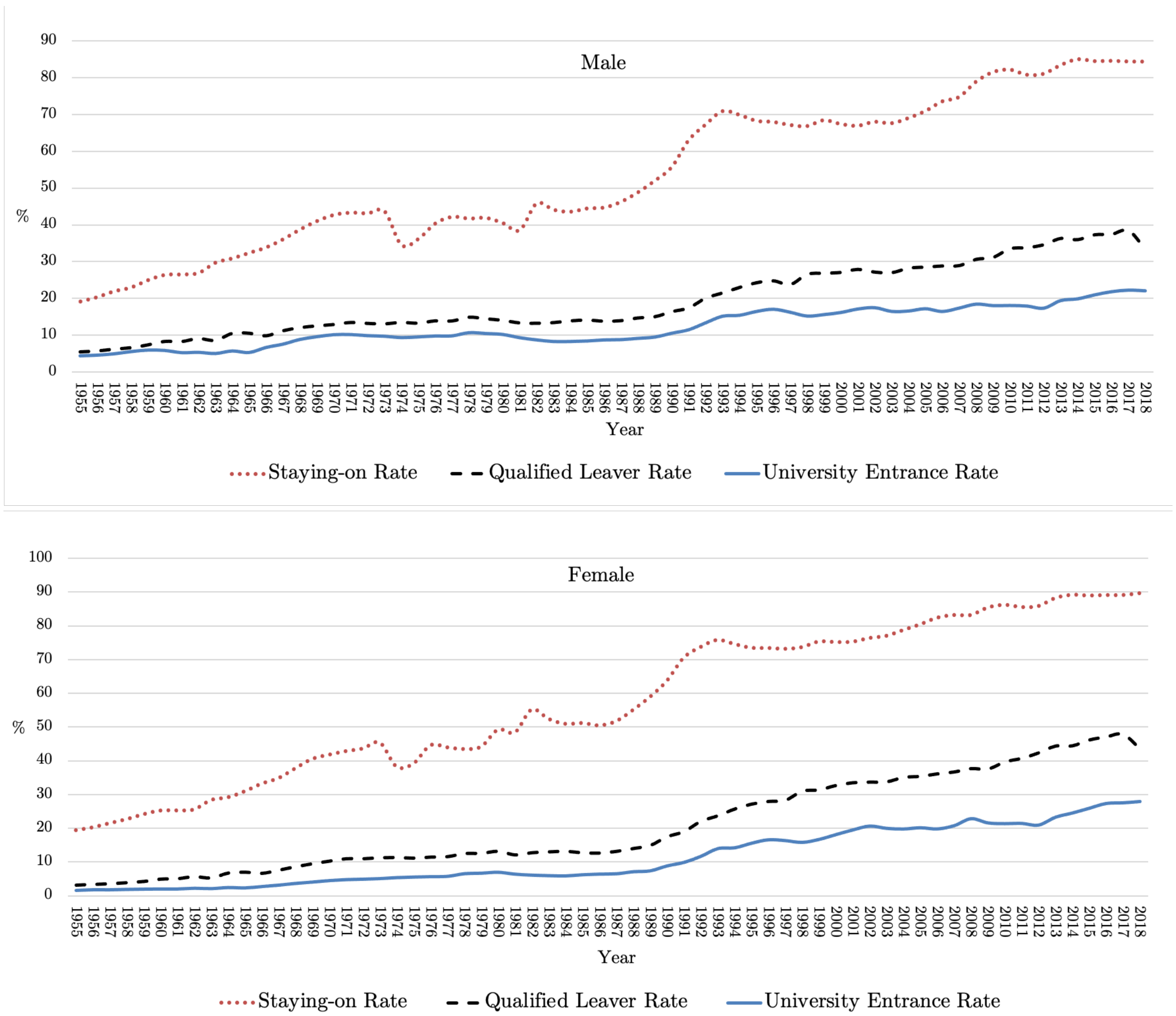
data series, our analysis will concentrate on those who obtain two or more 'A' levels passes.

[4]Pissarides (1982) provides a detailed explanation of these transitions in earlier years.

[5]The variables discussed in this paper mainly refer to England and Wales only. See Section 4 for further discussion of key variables.

[6]An obvious dip in the data occurs around 1974 due to relevant policy changes. It reflects an inconsistency in official statistics in subsequent years as a result of changed definitions of age groups. This will be discussed in greater detail in Section 4.1. Also worth mentioning is that the qualified leaver rate dropped in 2018 due to recent changes in government policies (newly reformed GCSE in 2017) and statistical methods (new 16-18 school and college accountability system in 2016).

Figure 1: Staying on Rate, Qualified Leaver Rate, and University Entrance Rate



Sources:

Statistics of Education

Statistics of Education, School Leaves, CSE and GCE

Statistics of School Examinations, GCSE and GCE

Statistical First Releases (Department for Children, Schools and Families) rate.

Notably, women's university entrance rate in the most recent year of the data (academic year 2017/18) is 27% greater than men's. This is comparable to the equivalent figure for the HEIPR in the same year, which amounts to 28%.[7] This gender gap can be seen more clearly in Figure A.2 of Appendix A, which shows that the 1990s saw women overtaking men among college applicants and entrants, alongside the substantial funding reforms. Since then, overall the gender difference in university applications and enrollments has kept rising, with the former reaching a record high in recent years.

These trends imply that, compared to male students, nowadays female students are more likely to apply to and enroll at universities. It could be that in general women benefit more from the HE funding reforms, in particular from the student loan policies in terms of the loan repayment threshold, repayment period, and write-off. This is because, compared to men, women usually opt for degree subjects associated with lower earning potential (Campbell et al., 2022), consistently earn less in the workforce, and tend to work for fewer years over their lifetime. As a result, women's lifetime earnings are estimated to be lower (Crawford and Jin, 2014). Indeed, as Dearden et al. (2008) suggest, HE funding reforms have substantial distributional effects differentiated by gender. For women with the lowest lifetime earnings, the reforms have actually reduced their costs of HE. Given these differences across gender, which cannot be directly detected by considering the entire population, we define most of the variables by gender to facilitate gender comparisons in evaluating policy changes. We then estimate our model and present the results separately by gender.

Another widespread concern is the gap across socio-economic groups, and in particular whether students from lower social class backgrounds would be underrepresented with these HE finance policy changes. Dearden et al. (2014) show that maintenance grants are not effective in narrowing the socio-economic groups gap in participation. While Murphy et al. (2019) find no apparent evidence that the substantial reforms in HE finance have widened the socio-economic gap in participation, in line with the findings from several other studies such as Blanden and Machin (2013), Crawford et al. (2016), Sá (2019), and Azmat and Simion (2021). However, our paper is unable

[7] See HEIPR published by the Department for Education. Source: `https://explore-education-statistics.service.gov.uk/find-statistics/participation-measures-in-higher-education#releaseHeadlines-tables`.

to comment on this aspect of the debate on the demand for HE as participation rates in full-time post-compulsory education by social class are not available on a consistent basis over the whole time period under study. In our analysis we use an alternative aggregate variable, per capita consumption expenditure, to capture the variance in schooling decisions due to changes in family income over time, which is to be further discussed in Section 4.2.[8]

The contribution of this paper is three-fold. First, existing literature relating to the HE funding policies has mainly examined one or a few reforms based on cross-section or panel data, usually over a relatively short period of time and in isolation from other related policy changes. However, if all young people face the same financing arrangement at a given point in time, then it will be difficult to identify the underlying relationship between the cost of HE and the demand for HE. This paper aims to fill this gap by providing a time-series analysis over the time period from 1955 to 2018.

Second, modeling long-run time-series data of aggregate variables relating to the education system is inherently problematic as these data are usually trended and predominantly influenced by legislative or structural changes and institutional reforms. This means that the data are invariably non-stationary and difficult to model without investigating the timing of these structural changes explicitly. Given the great variation in HE policies over the past six decades, our analysis accounts for structural breaks in testing the stationarity of the variables. Moreover, we allow for structural shifts when estimating our model by exogenously detecting the timing of the breaks.

Third, our paper examines young people's three-stage schooling decisions. The dynamic nature of schooling choice has been shown to play a crucial role in young people's decision-making (Stange, 2012; Heckman et al., 2018). A recent study by Belfield et al. (2020) adopts the setting of sequential schooling decisions in their study of teenagers' educational aspirations. Yet little research has focused on this sequential selection in evaluating the causal effects of funding reforms. Our paper addresses this issue and investigates young people's sequential educational decisions past the compulsory minimum school leaving age. In particular, we use the Seemingly Unrelated Regressions model to estimate a system of equations of the post-16 staying on rate, the qualified leaver rate, and the university entrance rate.

[8]For future work we will refer to administrative data, official statistics, and other sources for relevant information on participation by socio-economic groups.

Within such a framework, our empirical analysis suggests a significantly negative but quantitatively small impact of net college cost on HE participation, especially for girls. In particular, we evaluate the consequence of a rise in tuition fees by £1,000, *ceteris paribus*, and find that the university entrance rate would decrease by 1.37 and 0.37 percentage points for boys and girls respectively. The influence for girls is closer in size to the evidence found by Azmat and Simion (2021) who observe that the overall enrollment decreases by 0.5 percentage points as a result of either the 2006 funding reform or the 2012 funding reform. In addition, our elasticity of demand with respect to fees is estimated to be -0.121 and -0.026 for boys and girls respectively. The finding is broadly comparable to Sá (2019)'s estimated elasticity of applications regarding the 2012 reform, which is -0.11, but is smaller in magnitude than her estimated elasticity of -0.36 with respect to the reforms over the past two decades.

The remainder of this paper is organized as follows. Section 2 briefly describes the HE reforms over the past six decades and related policy concerns. Section 3 discusses the existing empirical work on the demand for post-compulsory education and HE participation. Section 4 describes the data and discusses the stationarity of data. The methodology to detect and estimate the break changes is outlined in Section 5. Section 6 discusses the empirical results and presents policy simulations. Section 7 concludes.

2 Policy Context and Related Discussion

2.1 Policy Background

Prior to 1998, most Local Education Authorities (LEAs) paid students' HE tuition fees and provided them with maintenance grants. When HE participation increased steadily during the 1980s and 1990s, the total amount of necessary funding did not rise in line with the HE expansion and it became untenable to subsidize HE. New HE finance policies were formulated to shift part of the cost of HE to the individuals. In the 1990/91 academic year, mortgage-style student loans were first introduced for HE students to partially replace grants and provide extra resources towards living expenses.

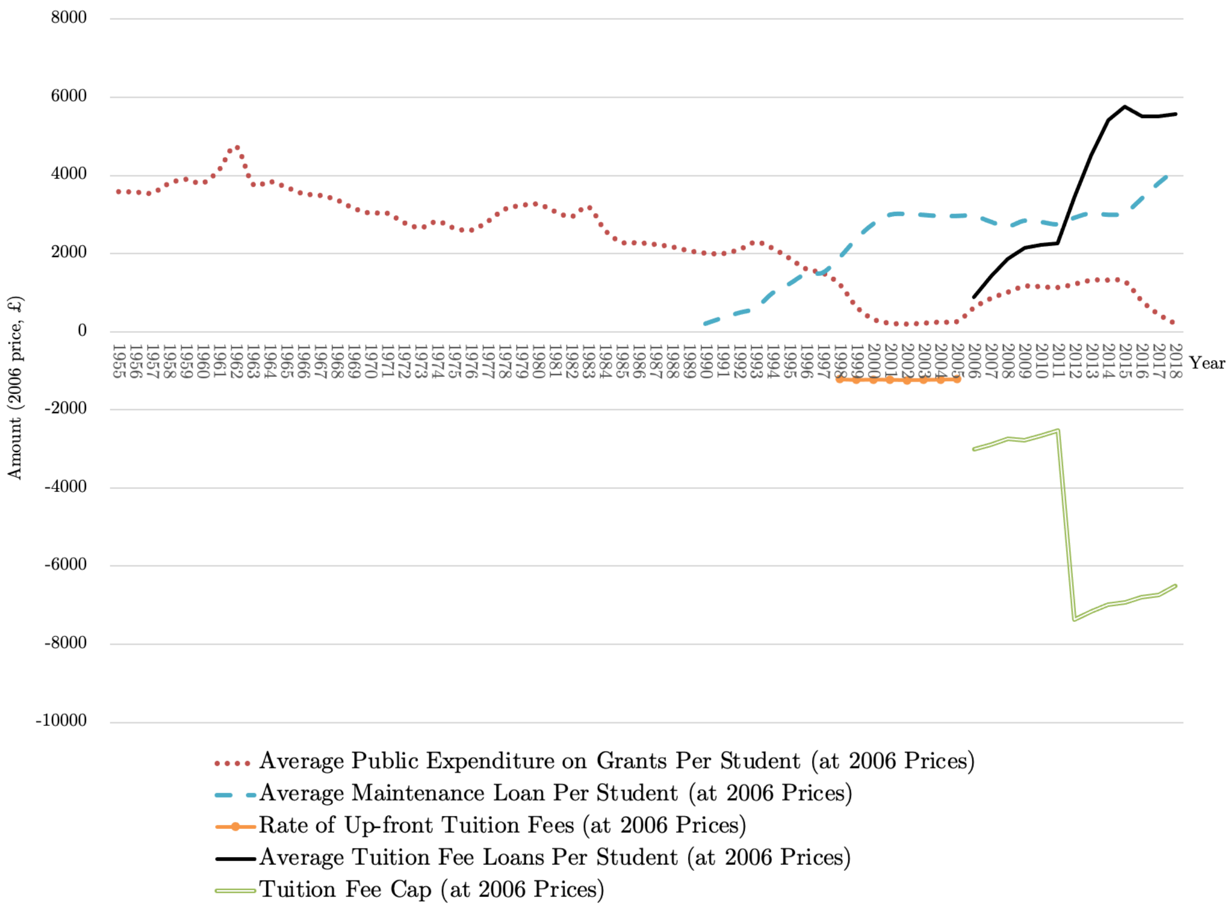
The 1998 reform: In the academic year of 1998/99, following the Dearing Report, a new HE student finance scheme came into effect. New entrants to full-time undergraduate courses were required to pay up-front tuition fees of up to £1,000 per year. In the same year, income-contingent loans were introduced to replace the mortgage-style maintenance loans. Under the new income-contingent repayment scheme, students are expected to repay the loans after graduating when their income reaches the minimum earnings threshold.

The 2006 reform: Further reforms took effect under the Higher Education Act of 2004. In England and Wales, the Higher Education Grant was introduced in 2004/05; it was replaced by a new maintenance grant in England two years later. Variable fees were introduced in 2006/07, up to £3,000 per year in England and up to £1,200 in Wales. The fee cap in Wales increased to £3,000 one year later. Undergraduate students do not have to pay the tuition fees upfront; government-subsidized fee loans were introduced so that tuition fees are repayable after graduation, when graduates are liable to pay back 9% of their income above the repayment threshold. With fees rising in line with inflation, the tuition fee loans, the interest rate charged, and the repayment threshold were adjusted accordingly.

The 2012 reform: In 2010 the Browne Commission recommended broad changes to university funding. The tuition fee cap rose several times, accompanied by significant changes in HE student funding policies. Among these reforms were the public funding cuts for teaching. To make up for the decline in teaching grants, universities in England and Wales were allowed to charge students substantially higher tuition fees from the academic year of 2012/13, up to £9,000 per year.[9] In order to meet the higher fees, adjustments were also made to the terms and conditions of tuition fee loans. In England, the repayment threshold was raised from £15,795 to £21,000, the repayment period (before write-off) was extended from 25 years to 30 years, and a positive real (above-inflation) interest rate was introduced: 3% while studying and up to 3% after graduation (Crawford and Jin, 2014). Later in the academic year of 2016/17, the cap on tuition fees was further increased to £9,250 in England, with most HE institutions setting fees at the maximum level.

[9] Wales-domiciled new entrants were also entitled to the Tuition Fee Grant to make up the difference in fee costs. Therefore Welsh undergraduate students attending any publicly funded UK university or college were not subject to the rising fee costs as much as the England-domiciled new entrants. In fact, there has been a great diversion in student support policy between England and Wales since 2006/07. But given that this time period is relatively short in the entire period under study and that Welsh students make up a relatively smaller proportion of the whole HE population, for recent years we focus on the HE policies in England.

Figure 2: Student Grants, Loans, and Fees



Sources:

Statistics of Education: Finance & Awards

Statistics of Education: Student Support England and Wales

Statistics of Finance & Awards

Statistics of Education: Finance & Awards

Statistical First Releases (Department for Children, Schools and Families)

Student Support for Higher Education in England

Student Support for Higher Education in Wales

Figure 2 plots the long-run trends of student grants, loans, and fees over the past six decades. Among these trends, student grants, measured by the average LEA expenditure (later "public expenditure") on maintenance grants per student, fell gradually from 1993, and by the mid-1990s had fallen dramatically by 42% since 1980. It remained relatively low after 2001 until 2006 when maintenance grants were reintroduced.[10] Besides, over the period from 1990 to 2000, the average level of maintenance loans continued to rise; ever since then, it remained stable until recent years.

An issue in estimating the causal effect of the HE finance policies on the demand for post-compulsory education in a time-series framework is that, throughout the time period under study, there has been a sequence of other policy changes that might have had important impacts on the participation rates and other key variables. For instance, school leaving age, namely the legal age at which a child is allowed to leave compulsory education, was raised to 16 in 1972.[11] In subsequent years, the post-16 staying on rate increased. Besides, in 1988, the dual system of O-Levels and CSE exams in the UK was replaced by a new system, GCSE. This unified exam put all children on the same scale, with a range of seven grades from A to G. The establishment of GCSE resulted in the proportion of the cohort achieving five or more GCSEs at grade C or above (or the equivalent of this prior to 1988) increasing substantially. And this appears to correspond to a significant upward shift in the trend of the qualified leaver rate and the university entrance rate as reflected in Figure 1. Furthermore, following the Further and Higher Education Act 1992, a number of former polytechnics and other institutions (mainly colleges of higher and further education) gained university status (often referred to as "post-1992 universities"). The following years saw a significant expansion of HE.

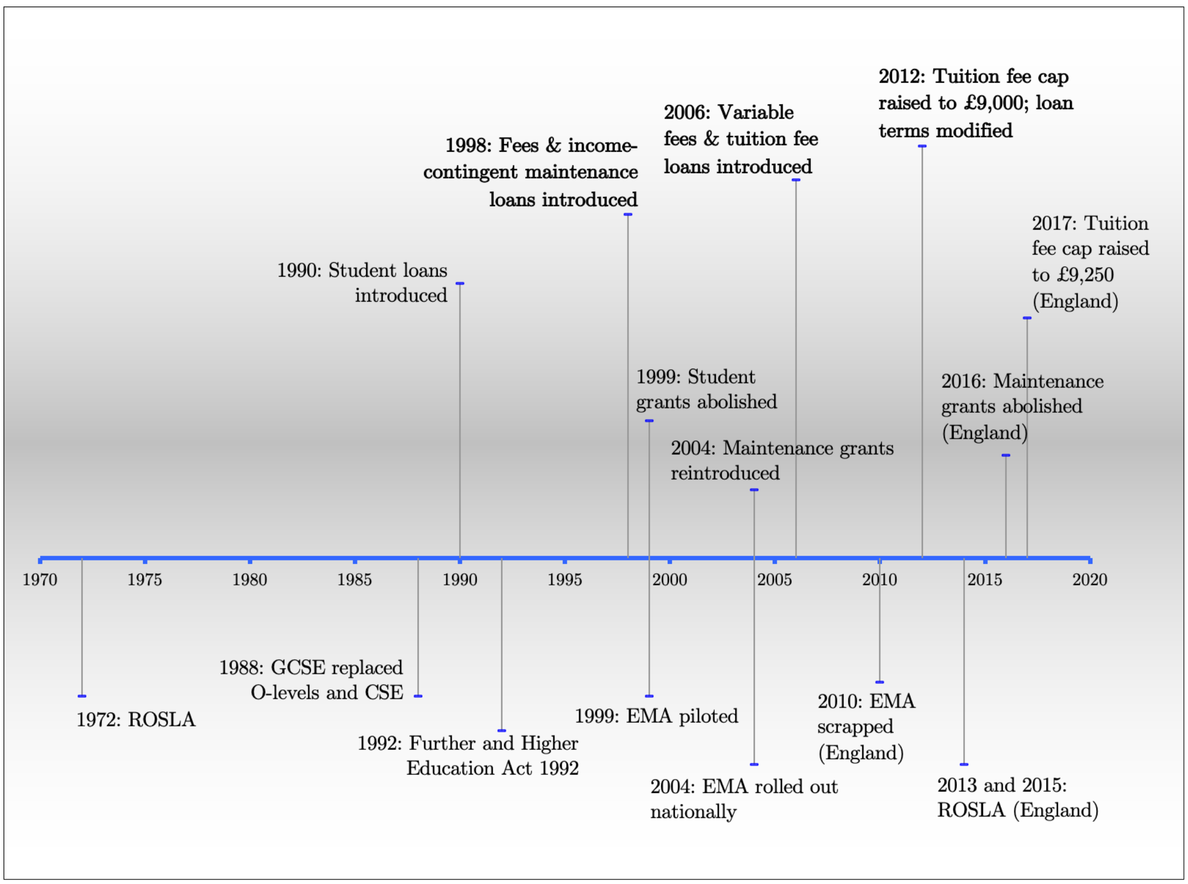
In addition, the Education Maintenance Allowance (EMA) was introduced in England in 1999. The EMA is a means-tested program applicable to 16 to 19-year-olds

[10]The definition of this variable has changed over time. It is defined as "average LEA expenditure on maintenance grants" up to academic year 1997/98, and "average public expenditure on maintenance grants" from 1998/99 to 2008/09. In subsequent years, only combined data is available for the expenditure on maintenance, HE, and special support grants. The Higher Education Grant was introduced in England and Wales in 2004/05. The Special Support Grant was introduced in 2006/07 and in certain circumstances replaced the Maintenance Grant. It was removed for new full-time students in 2016/17 in England. Figure 2 reflects this policy change: the average expenditure on grants creeps up around 2006 and then decreases from 2016.

[11]In England, school leaving age was raised to 17 in 2013 and further raised to 18 in 2015.

from lower socio-economic groups. It provides financial support to these young people to stay on in full-time education beyond the statutory school leaving age of 16. The EMA was rolled out nationally in 2004, before it was scrapped in England at the end of academic year 2010/11. The EMA has been shown to be effective not only in encouraging young people's initial participation but also in retaining them in full-time education in subsequent years (e.g., Dearden et al., 2009). Therefore this policy might also have been linked to a shift in the staying on rate.

Figure 3: Timeline for Relevant Policy Changes



Notes: From 2006/07 some policies are different in Wales, which are not reflected in this timeline. Important policies include:

(i) new Assembly Learning Grant was introduced 2006/07 in Wales;
(ii) the maximum fee which HEIs can charge remains £9,000 in Wales;
(iii) the EMA is now still available in Wales.

All these important policy changes are summarized as a timeline in Figure 3. These substantial changes in education policies might be linked to structural changes, i.e., statistically robust shifts in means and trends, in the demand for post-compulsory education and other key variables. If that's the case, then the traditional unit root tests are likely to be biased and lead to false test results. Moreover, structural shifts could also be linked to the multi-equation system we are going to examine. In the presence of such changes in a system of equations, it is crucial to detect the timing of these breaks so as to obtain robust estimation results. We will provide more details in Section 5.

2.2 Supply of University Places

It should be noted that our analysis takes as given and unconstrained the supply of university places, despite that enrollment caps were once in place which set maximum allowable student numbers for higher education institutions. Student number controls were introduced in 1993 on account of the growing student numbers under the free HE system. However, these controls were soon relaxed in 1998 alongside the introduction of tuition fees. They were further relaxed in 2012 and 2013 when tuition fees soared and were finally abolished in 2015. Moreover, our calculations suggest that after 1994 a roughly constant fraction of 75-80%[12] of applicants to university succeed in getting in. And we posit that this is consistent with unconstrained supply if we allow for applicants who fail to make their 'A' level grades or who decide not to go to university or defer entry. In some sense, the 'raw' demand for university places is the total number of young people applying to university. However, this number is not the true demand as a sizeable fraction of the applicants either do not obtain 2 'A' level passes or the necessary grades for their chosen course. These applicants who are unable to go to university by reason of insufficient qualifications should not be added into any calculation of the demand for places.

While student number controls remained in effect to limit the numbers of UK-domiciled undergraduates, UK universities saw a surge in international student enrollments, and consequently foreign students, who often pay higher fees than home students, have become a major source of revenue in the UK HE system (Murphy, 2014). Therefore, another important factor related to the supply of university places

[12]We provide more details of this in Appendix A.

is how the rapid growth in international student numbers can affect domestic student numbers. Machin and Murphy (2017) find no crowd-out effect on domestic undergraduates from the influx of overseas students. Their findings are supported by evidence from related studies in the US (e.g., Shih, 2017; Chen, 2021). Notably, the period of time the authors examine covers academic years 1994/95 to 2011/12 which had seen a boom of international students in the UK, concurrent with the measures to limit the number of UK and EU-domiciled undergraduates. In this sense, the dramatic inflow of international students over recent years does not seem to affect the supply of university places.

A future issue is whether any limitation on the supply of places has curtailed demand from students who think they will be unable to find a university place. Our analysis cannot hope to model this inevitable interaction of potential supply on "discouraged demand." However, we suggest that since supply of university places has been relatively unconstrained (specially in terms of LEA maintenance funding to individual students up to 1999),[13] then this will not detract from our analysis.

3 Related Research

3.1 HE Finance and HE Participation

There is a lot of evidence from the US on the relationship between HE finance and HE participation. Many of these studies are facilitated by a variety of changes in state or federal financial policies in post-secondary education. Overall, lower college cost is associated with an increase in college enrollment (e.g., Dynarski, 2003; Kane, 2007; Denning, 2017; Dynarski et al., 2021). Whereas influences are found negligible among low-income students for converting loans to grants (Linsenmeier et al., 2006) or tuition deregulations (Andrews and Stange, 2019). Furthermore, offering free tuition does not seem to have discernible effects on enrollment (Nguyen, 2019).

There are several studies in the UK context that explicitly evaluate the effects of changing tuition fees and student financial support. Blanden and Machin (2004) study temporal shifts in HE participation and attainment of children from different parental

[13] Any student who obtained a university place prior to 1999 was automatically guaranteed a maintenance grant from their Local Education Authority.

income groups. They use longitudinal data that cover the period from the early 1970s to the late 1990s when the UK HE experienced a rapid expansion and the HE financial policy gradually became less generous to students. They find a growing imbalance in access to HE by income group as HE expanded, indicating that the participation gap was widened between rich and poor children.

Galindo-Rueda et al. (2004) examine the socio-economic gap in HE participation over the period from 1994 to 2001, when up-front tuition fees were introduced and student support gradually reduced. Based on postcode level data, their results suggest that richer postcodes experienced a more rapid increase in HE participation than poorer neighborhoods in the early 1990s, prior to the introduction of fees. Using micro-level data from the Youth Cohort Study (YCS), they provide evidence of lower socio-economic backgrounds resulting in a lower probability of participating in HE, and this inequality increased over a longer period of time.

Dearden et al. (2008) examine the substantial HE funding reforms introduced by the 2004 Higher Education Act in England. Using simulated data on lifetime earnings, they find that there has been a significant reduction in HE costs over the life cycle for students from low-income families and an increase in the costs for those from middle and upper-income families. On the other hand, HE costs are estimated to be lower for female graduates with the lowest lifetime earnings, whereas graduates with higher earnings generally expect themselves to incur a higher cost for their HE.

In a more recent study, Dearden et al. (2014) evaluate a policy change in 2004, which reintroduced means-tested maintenance grants for students from poor family backgrounds. Based on the cross-sectional UK Labour Force Survey (LFS) data from 1993 to 2006, they investigate the causal effect of the reform on first-year degree enrollment in a difference-in-difference framework. The authors find positive effects on HE participation, with a £1,000 rise in maintenance grants increasing enrollment by 3.95 percentage points. The scale of this impact is consistent with the evidence from other countries such as Dynarski (2003) and Nielsen et al. (2010). On the other hand, the reform does not significantly reduce the socio-economic gap in enrollment.

Sá (2019) focuses on the increased tuition fees and other changes in HE financing in England in 2012 within a difference-in-differences framework. Using administrative data linked to data from the Higher Education Statistics Agency (HESA) Destinations of Leavers from Higher Education (DLHE) survey, the paper finds short-run decreases in both application and attendance in response to rising fees, with elasticity of demand of -0.36 for enrollment. The reduction differs across institutions and subjects, being larger in magnitude for less selective universities and courses with lower future pay and employment rate.

Azmat and Simion (2021) exploit the 2006 and 2012 HE financing reforms and investigate the impact on demand for HE in England for the period between 2004 and 2013. Combining three data sets, they examine the impact of the reforms on enrollment and students' HE choices. They find that the overall enrollment decreased by 0.5 percentage points, and the 2006 reform reduced the gap in participation across socio-economic groups.

Most of the aforementioned studies take advantage of discrete changes in HE student financing policy, namely over a relatively short period of time and usually in isolation from other related policy changes. However, given the lengthy and multifaceted features of these policies, an extensive analysis that covers a long period of time and different aspects of the system will help better understand and assess the long-term impact of policy changes. Murphy et al. (2019) provide such an integrated study. They descriptively analyze the trends in HE enrollments in England after tuition fees were introduced to the HE system. The authors conclude that HE enrollment rate continued to increase despite the substantial changes in HE finance policies, whereas the socio-economic gap in college enrollment appears to remain stabilized after years of widening inequality. Notably, as opposed to focusing on the net prices of university participation, the authors emphasize the importance of accounting for the net liquidity available to students to cover their living expenses. In particular, they examine the net liquidity by evaluating the resources accessible to university students against the costs of attendance. Their analysis shows that, as a result of a set of finance reforms, students' net liquidity has risen over time, similarly across family income groups. Yet the increased net liquidity is still found to be insufficient to cover students' cost of living. We will discuss students' net liquidity further in Section 4.2.2.

3.2 Related Time-series Studies

Most of the existing research on the demand for HE is based on cross-section or panel data. However, it is difficult to identify the underlying relationship between the cost of HE and the demand for HE if all young people face the same fees and tuition costs at a given point in time. The alternative is to collate long-run time-series data over a substantially long period to identify regime changes in HE funding when examining the variation in participation rates over time. Looking at the literature, relatively few time-series studies have investigated the HE funding regime changes. Research in the UK context is mostly concerned with the post-compulsory education choices of young people at the age of 16 and examines the determinants of participation rates.[14]

Pissarides (1981) models the staying on rate between 1955 and 1978 and concludes that variations in the proportion of 16-year-olds attending post-compulsory education were mainly driven by changes in household permanent income and movements of relative earnings between manual workers and highly qualified workers. In another paper by the same author, Pissarides (1982) examines the transition from school to university. In addition to the determinants of the staying on rates, the study investigates the determinants of the proportion of the 18-year-old age group qualifying for university entrance, and the determinants of the proportion of the age cohort entering university for the first time. The result suggests that the school staying on rate is mainly driven by the relative present values of earnings from different educational qualifications, per capita consumption, and the unemployment rate. The major determinants of qualified leaver rate are the school staying on rate (two years earlier), the real permanent income (two years earlier), and the ratio of the present value of earnings of early school leavers to that of university graduates (one year earlier). And the qualified leaver rate is found to be a good indicator of variations in the demand for university places.

Whitfield and Wilson (1991) re-estimate Pissarides (1981)'s model over a longer period from 1955 to 1986, and find that the model specification becomes inadequate when applied to this later time period. They then extend Pissarides' work by adopting dynamic specifications, applying vector auto-regression techniques, and including additional explanatory variables to take account of changing social class structure, the rate of return to schooling, and the level of unemployment in the youth labor market. Their results suggest that these variables play a key role in determining the decision of post-compulsory education.

[14] The US literature also provides time-series analysis of college enrollments, such as Mattila (1982), and McPherson and Schapiro (1991).

McVicar and Rice (2001) adopt cointegration analysis to an extended period from 1955 to 1994, and examine how public policy interventions affected young people's decisions of post-compulsory education. They find a significant role for GCSE attainment and the expansion of the HE sector (as measured by the proportion of 18 and 19-year-olds going on to HE in the relevant year) in influencing the participation decision of 16-year-olds. Other important factors include changes in unemployment and the ratio of professional earnings to manual earnings.

Using a regional panel data over the period from 1975 to 2005, Clark (2011) assesses the determinants of enrollment in post-compulsory education in England. Overall the empirical results are robust to the addition and exclusion of control variables, and indicate strong positive effects of youth unemployment and GCSE exam achievement, especially for girls. He then aggregates the data to national level and estimates time series models. Without other controls, youth unemployment is estimated to have a strong and positive effect on enrollment. However, this effect is sensitive to the model specification: with other control variables added to the model, the magnitude of the youth unemployment coefficient becomes smaller in the boys' enrollment model, and the sign of coefficients for the girls' model is even reversed.

These papers present a consistent time-series framework highlighting the post-compulsory education choices of young people. But many of the earlier works predate the commonplace concern with stationarity of the stochastic time series variables. Whitfield and Wilson (1991) are among the first to address the issue of stationarity. Several following papers account for the stationarity but do not consider structural changes in the variables. In fact, the modeled relationships usually treat the break dates as known, without performing relevant tests. Some studies use step dummy variables to capture important regime changes or decompose the sample on the basis of growth in enrollment. This is problematic since if a break date is chosen as known, then this choice cannot be treated as exogenous. In essence, any break point chosen by eyeballing the data is still arbitrary.

Although the examination of structural breaks is well-documented in time-series analyses,[15] to our knowledge it has not yet been used in evaluating the student support

[15] The seminal paper is the work by Perron (1989) who examines the testing for the unit root null hypothesis in a framework allowing for a one-time change in the level or in the slope of the trend function. The paper has induced many empirical studies in this area.

changes. In this paper, we fill this gap by taking into account structural breaks in evaluating the impact of policy changes. In particular, we allow for structural shifts in the series when running unit root tests. Furthermore, the estimation in this paper adopts the methodological developments presented in Qu and Perron (2007) to account for the regime changes in post-compulsory education policies. The framework developed by Qu and Perron, whereby the break dates are treated as unknown a priori, allows us to estimate these structural break dates exogenously, i.e., without imposing prior notions about their existence, number, or timing.

4 Data

Using time-series data from 1955 to 2018, this paper examines the role of different factors in driving the demand for post-compulsory education. Our data is collated from, or calculated on the basis of, various data sources which are detailed in the data appendix (Appendix H). The data used mostly relate to England and Wales except for a few variables over recent years, for which we focus on England only due to changing policies and definitions. Most of the data were collected separately for males and females with the exception of those related to the funding reforms, as most of the data on grants, fees, or loans are not available by gender.

4.1 Dependent Variables

Following Pissarides (1981; 1982), we define "staying on rate", denoted by S, as the proportion of 16-year-old age group attending full-time education in schools[16] and colleges of further education. The 16-year-old age group consists of people aged 16 on January 1, and who are above the minimum school leaving age in September of the same academic year. Therefore in our data, prior to 1972/73, when the minimum school leaving age was set at 15, the age group is composed of all 16-year-olds. And the staying on population consists of the number of 16-year-old pupils attending full-time education in schools and major further education establishments. In academic year 1972/73, the minimum school leaving age was raised to 16, and the staying on rates in subsequent years are defined as the 16-year-old age group above the minimum school-leaving age

[16]Including schools maintained by LEA, direct grant schools, and independent schools.

attending full-time education in schools. In other words, only those born between January 1 and September 1 are included in the data for these years.[17] It should be noted that, due to the change in the definition of the relevant age group for calculating S since 1972/73, the average age of the defined '16-year-olds' is higher after 1972/73 than that of the age cohort in previous years. And there turns out to be an obvious downward shift in 1972/73, as shown in Figure 1.

To evaluate the HE student finance policies we also examine those school leavers who are qualified to enter university and those who actually enter university. We define "qualified leaver rate", denoted by Q, as those qualified leavers with two or more 'A' level passes as a proportion of 18-year-olds.

The "university entrance rate", denoted by UE, is defined as new entrants to first-degree undergraduate courses in universities and colleges as a percentage of the 18-year-old age groups. It should be noted that our definition of UE is not based on the standard ones that are commonly used in official statistics, and hence is different from official participation indices such as the Age Participation Index (API) and the Higher Education Initial Participation Rate (HEIPR). The API and the HEIPR are higher because they cover more higher education institutions and are defined on the basis of different age groups. In particular, the API measures full-time participation by UK-domiciled students, aged below 21 years, in higher education courses in Great Britain.[18] While the HEIPR focuses on England-domiciled HE students who are aged 17 to 30. Students are counted if they participate for at least six months on a course that is expected to last for at least six months; whereas students are not counted if they participated in Higher Education previously for at least six months before the current year. Students at further education colleges (FECs) in England, Scotland, and Wales are counted if they are on courses designated as National Vocational Qualification Level 4 or above, or listed as Higher Education.[19]

[17] However, for academic years 1972/73 to 1978/79, official statistics (from Statistics of Education) only provide relevant data defined on the age at the beginning of calendar year (i.e. January in a specific academic year). Following Pissarides (1981; 1982), the denominator was taken to be two-thirds of the entire age group in the calculations of S for these years, by the assumption of a uniform birth distribution. No such adjustment is necessary for the data in subsequent years when relevant data are defined on ages at the beginning of the academic year.

[18] Source: "House of Commons Hansard Written Answers for 26 Jan 2006."

[19] Source: "Methodological Revisions to the Higher Education Initial Participation Rate."

4.2 Independent Variables

The academic attainment before the end of compulsory education is expected to exert an essential impact on higher education participation (Chowdry et al., 2013; Dearden et al., 2014). In our analysis, this prior educational attainment is measured by the proportion of the group achieving five or more GCSEs at grade C or above, or the equivalent of this prior to 1988. We expect that variations in qualified leaver rate (Q) are partially driven by this academic attainment.

Cross-sectional analyses have extensively discussed the causal contribution of family backgrounds such as parental income and socio-economic status. In this paper, we use an alternative aggregate variable to capture temporal changes in family resources. Early research (e.g., Lazear, 1977; Pissarides, 1982) highlights the consumption value of education in individual educational decisions. Education can be regarded as a normal consumption good and the demand for schooling is associated with family background and in particular increases with family income. Following Pissarides (1982), we use per capita consumption expenditure to represent permanent income.[20]

The current or expected labor market conditions can also influence the demand for education. Bradley and Migali (2019) observe that high unemployment areas are associated with a higher risk of drop-out. Tumino and Taylor (2015) suggest that the school enrollment of credit-constrained youths is more sensitive to labor market conditions than their counterparts from better-off families. To examine the impact of unemployment, we control for adult unemployment in our estimations.

For young people, another suitable indicator of labor market conditions is youth unemployment. The evidence of its influences remains mixed in the literature. On the one hand, a high youth unemployment rate translates into lower opportunity costs for staying on in school, and may discourage students from leaving school (e.g., Adamopoulou and Tanzi, 2017). On the other hand, youth unemployment may lower high schoolers' expectations about the value of a high school diploma, resulting in an increased risk of dropping out (Eckstein and Wolpin, 1999). Youth unemployment is usually defined as the unemployment rate of young people aged under 20. However, due to data limitations in earlier statistics, we use an alternative definition by computing the number of 18-19 year old unemployed as a percentage of the number of employees (i.e. labor force

[20] All monetary variables in this study are measured in real terms (at 2006 prices).

participants) of the age cohort. The long-term trends in these unemployment rates are depicted in Figures B.1 and B.2. In our estimation setting, either youth unemployment or adult unemployment enters the S equation as an indicator of labor market conditions that youths are faced with.

In addition, we include in the model the unemployment rate of new university graduates which is assumed to be related to Q and UE. More specifically, the graduate unemployment rate is the percent unemployment of UK-domiciled graduates who obtained undergraduate qualifications through full-time study. The long-run trend of graduate unemployment is shown in Figure B.3. The potential effect of graduate unemployment is somewhat ambiguous. On the one hand, the variation in undergraduate unemployment will influence the 18-year-olds' expectation of future employability. And a higher graduate unemployment rate should thus induce a negative effect on the demand for education. The magnitude of this effect should depend on the extent to which young people treat it as an indicator of future labor market conditions. On the other hand, graduate unemployment is related to youth unemployment and adult unemployment, and therefore also reflects the possibility of being currently employed. In this respect, it may exert a positive effect on the demand for education.

The expected rate of return to additional schooling has been identified as an important determinant of the demand for HE and therefore is incorporated into the model. This could be represented in the form of the internal rate of return (IRR) to undertaking a graduate job. The variable is constructed on the basis of LFS, New Earnings Survey (NES), and Wilson (1980, 1983, and 1985)'s estimates for earlier years. The methodology for calculating follows Ziderman (1973), Wilson (1980, 1983, and 1985), and Dolton and Chung (2004). Briefly, the IRR is found by solving for r in the following expression,

$$\sum_{t=16}^{65} \frac{B_t - C_t}{(1+r)^{t-15}} = 0, \tag{1}$$

where B_t is the earnings from undertaking a graduate job and C_t is the foregone earnings that the individual could have earned in a non-graduate job. Further details regarding how we define graduate and non-graduate jobs can be found in Appendix C. Figure C.1 graphs our estimates of the IRR over the duration of our sample years. It shows a rising trend during the 1980s through the late 1990s, which is consistent with Blanden and Machin (2004)'s findings. In the 2010s, there was a decline in the monetary gains from a college degree, which could have partly resulted from the significantly higher tuition fees.

4.2.1 Net College Cost

Financial aid is provided for HE students to reduce their cost of attendance and alleviate their liquidity constraints. As our focus will be on the effect of HE finance policy changes, two factors we take note of are *net college cost* and *net liquidity*. We now detail how we define these variables. We begin by describing three elements that are associated with the cost of attending university: student grants, student loans, and tuition fees.

Student grants: Demand for post-compulsory education is expected to increase with direct subsidies that are available to students. We use the average annual "LEA expenditure" (or "public expenditure" in recent years) on maintenance awards per student as a proxy for student grants. To the best of our knowledge, this is the most consistent aggregate data that is available to capture the time-variation in student grants.[21] From a student's perspective, student grants are important sources of financial aid that need not to be repaid. Thus prospective undergraduate degree students have a strong incentive to acquire information on student grants, and may pay particular attention to broad trends in student supports over the past few years. Meanwhile, HE finance policies are generally announced ahead of university application deadlines, and thus university applicants usually have access to related information when they make their HE decision, from various sources of information such as schools, universities, and social media. Therefore, we assume that prospective students are aware of the average level of student grants and form their expectations of college prices accordingly. As such, data on average awards reflects students' prediction of individual financial aid.

Student loans: Two types of student loan are to be considered next, maintenance loan for living costs and tuition fee loan. In the 1990/91 academic year, mortgage-style maintenance loans were introduced to partially replace grants. In September 1998, the

[21]Similar data has been used to measure financial aid in the US literature. For instance, while calculating the net prices that students actually pay for college education, Dynarski et al. (2022) approximate the level of financial aid with average grant aid per student. In examining trends in net prices, they highlight the key role of average grant aid in keeping net prices relatively stable over recent years.

mortgage-style loans were superseded by income-contingent loans. Maintenance loans are supposed to provide extra resources towards HE students' living expenses; while young people have to incur living expenses irrespective of whether they pursue HE or not. Therefore, we do not take the repayment of maintenance loan into account when calculating college costs. On the other hand, students do incur interest on their loans, which could entail a rise in college costs. However, we cannot incorporate the interest payments in our calculation prior to 2006/07 due to the lack of relevant data. The other type of student loan, namely tuition fee loan, was introduced in the academic year of 2006/07 alongside the implementation of variable fees system, so we now turn to a discussion of tuition fees and then fee loans.

Tuition fees: Tuition fees stand for an important form of college costs, and one can reasonably expect that increased university tuition fees will dampen young people's willingness to stay on in school and as a result deter HE participation.[22] Prior to 1998, HE was provided free for students. In the academic year of 1998/99, fixed fees system was implemented in England and Wales. New entrants to full-time undergraduate courses were required to pay up-front tuition fees of up to £1,000 per year. The rate of fees increased in line with inflation in subsequent years, until 2006/07 when variable fees system was implemented. Under the new system, students do not have to pay their tuition fees upfront; alternatively, they can take up government-subsidized tuition fee loans to defer tuition fees after graduation, when their income reaches a repayment threshold.

To approximate additional fee costs incurred in taking up tuition fee loan, we draw upon the data from the Institute for Fiscal Studies (IFS) on graduates' lifetime loan repayments. The data is calculated using IFS's graduate repayments model (Crawford and Jin, 2014). The model incorporates the changes to various parameters of student loans - including "the interest rate, the repayment threshold, the repayment period and the repayment rate" - which are closely related to the long-term cost of student loans (Crawford et al., 2014). In particular, the IFS data we use for our analysis is the net present value (NPV) of graduates' loan repayments over their lifetime, discounted at 0.7% plus Retail Price inflation and defined for full-time England-domiciled new entrants to UK universities studying for an undergraduate degree (Britton et al.,

[22] Although university students also incur other costs of attendance such as food, books, accommodation, and transportation, we ignore these because of the lack of consistent data.

2020).[23]

Several considerations justify our use of the NPV of fee loan repayments as a proxy for tuition fee costs. First, using NPV repayment helps to maintain data consistency. Under the current variable fees system, not all HEIs actually charge the cap of tuition fees, and thus the level of maximum fees does not make an ideal proxy for fee costs. On the other hand, the NPV of repayments approximates the real value of tuition fees. In essence, it is more consistent with the upfront tuition fees data used for the earlier fixed fees system. Second, we employ the NPV repayment instead of the university sticker price, the latter also referred to as the "cost of attendance" including published tuition as well as miscellaneous expenses. Because of the income-contingent nature of the present fee loan system, sticker price does not eventually translate into what an individual graduate actually repays. Instead, to a great extent it represents notional debt and hence exerts a limited effect on students' expected repayment. Whereas the NPV of loan repayments effectively reflects the real values of fees and is therefore more informative in measuring the true college costs.[24] Third, information about loan repayment terms is publicly available, and based on this information, prospective college students could readily form their expectations of college cost.[25] Besides, they can turn to online student finance calculators (and student loan repayment calculators) which provide personalized estimates of college costs.[26] If prospective college students are rational and understand loan repayment terms, then the NPV repayment, which reflects graduates' expected lifetime loan repayment, will be superior to sticker price in evaluating the impact of college cost on the demand for HE.

Using this total repayment data, we proceed to calculate fee loan repayment as

[23]Note that IFS does not in general publish projections for multiple cohorts. The data used in this paper are unpublished rough estimates underlying Table 5.1 in Britton et al. (2020).

[24]In fact, the sticker price usually exceeds the actual cost that is incurred for university education (Crawford et al, 2016). And changes in net college cost are likely less than changes in the university sticker price (see, e.g., Turner, 2004).

[25]In a DCSF Longitudinal Study of Young People in England (LSYPE) survey, the majority of the prospective HE students considered themselves to be informed about financial support in HE: among 4,928 respondents, 51.6% of them thought that they were "fairly well informed", and a further 13.8% believed that they were "very well informed" (Bates et al., 2009).

[26]For instance, *the United Kingdom public sector information* website and the *IFS* website both provide student finance calculators; and various other websites provide student loan repayment calculators.

the total repayment minus maintenance loan repayment, with the latter approximated by the actual average amount of maintenance loan taken up by students. Moreover, based on what we've discussed, there are clear rationales for calculating the net college cost separately for the three fee regimes. (i) For the "free college" regime up to 1997 (1955-1997 in our sample of data), student grants are the only student finance element under consideration which take negative values. (ii) For the "fixed fee regime" (1998-2005), we employ the real rate of tuition fees charged to university entrants each year as a measure of tuition fees. Student grants are also included for this period. (iii) For the"variable fee" regime (2006-2018), in addition to grants, we account for fee loan repayments which are measured by graduates' expected lifetime repayments of fee loans as described above.

Remark. Note that for the second regime we omit the loan interest (charged for maintenance loans) because relevant data is unavailable, whereas this is not the case for the latest time interval for which the IFS's loan repayment data is used, as the IFS modelling has implicitly taken account of the loan interest payment. In particular, there is no separation in UK's student loans system between payment of interest and repayment of principal, and accrued interest is simply added to the loan balance. Besides, even though the interest rates were increased for higher-earning graduates in the post-2012 system, this has no bearing on the repayment made by graduates in a given year, which is set at 9 percent of the gross income above the repayment threshold.

Moving forward with these three fee regimes, we define net college cost as

$$COST = \begin{cases} -grant & (1955-1997) \\ upfront\ fees - grant & (1998-2005) \\ fee\ loan\ repayment - grant & (2006-2018), \end{cases} \tag{2}$$

where $fee\ loan\ repayment = total\ loan\ repayment - maintenance\ loan.$

4.2.2 Net Liquidity

When it comes to evaluating funding policies, the net liquidity available to enrolled university students is also an important factor to account for. Great Britain's tuition fee reforms are accompanied by an income-contingent repayment scheme. The new student finance arrangements alleviate credit constraints for students, thereby increasing their net liquidity. Young people may make their enrollment decisions by weighing the possible resources they can access in the foreseeable future against the estimated costs of attendance. Murphy et al. (2019) address this issue and explicitly examine the net liquidity available to university students during their studies. In their study, college students' net liquidity is computed by subtracting up-front fees from the sum of grants and maintenance loans. Fee cost is set at zero from academic year 2006/07 onwards, after upfront fees were replaced by variable fees. Following their work, we define the net liquidity variable as[27]

$$LIQUIDITY = \begin{cases} grant & (1955-1989) \\ grant + maintenance\ loan & (1990-1997) \\ grant + maintenance\ loan - upfront\ fees & (1998-2005) \\ grant + maintenance\ loan, & (2006-2018). \end{cases} \tag{3}$$

Figure 4 displays the long-term trend in net college cost and net liquidity over the past six decades.

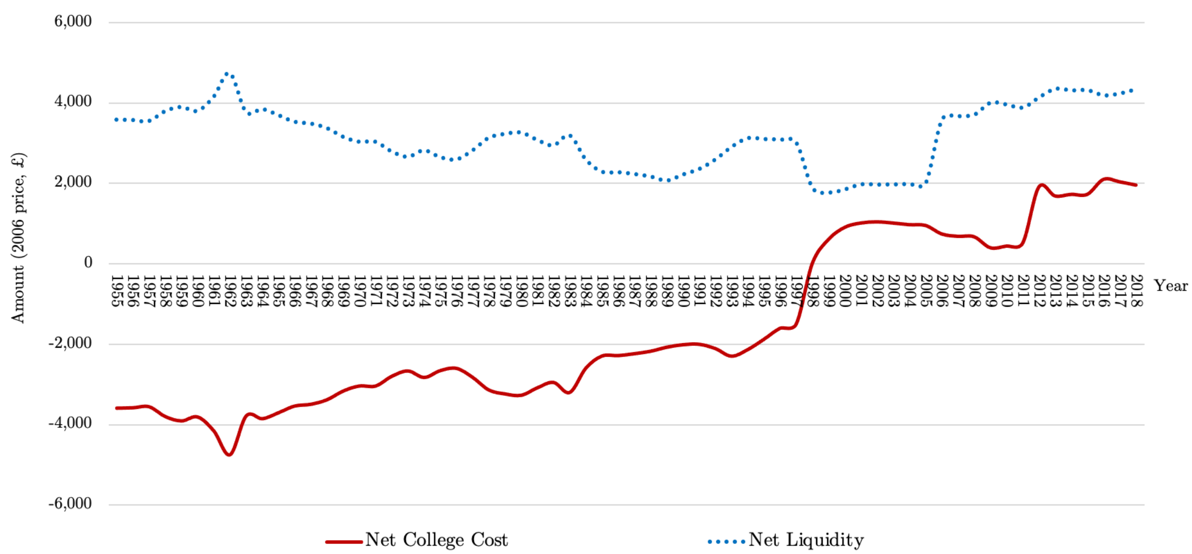
5 Methodology

5.1 Unit Root Tests Allowing for Structural Changes

Natural log transformations are taken for all variables except the net college cost which is negative for earlier years. To circumvent the possibility that our regression analysis may give rise to spurious relationships, we first carry out Augmented Dickey-Fuller unit root tests to check the stationarity of each variable. A well-known weakness of the Dickey-Fuller style unit root test is its inability to account for structural changes in the variable itself. In the presence of structural shifts, the test will be biased towards the nonrejection of the unit root null. It is therefore particularly crucial to take account of structural changes in our unit root analysis, since most of the series of variables in our study appear to exhibit some sort of structural changes. In fact, these structural changes are evident by even a casual examination of the time series plots of staying on

[27] It should be noted that parental contributions should also be considered as one of the components when calculating students' liquidity. However, we don't incorporate parental contributions here due to the lack of data.

Figure 4: Net College Cost and Net Liquidity



rate (S), qualified leaver rate (Q), and university entrance rate (UE) as in Figure 1. To overcome this complication, we then perform alternative unit root tests allowing for structural changes, namely Zivot-Andrews (1992) and Clemente-Montanes-Reyes (1998) tests, as robustness checks for the Augmented Dickey-Fuller tests. Our test statistics are reported in Tables D1-D3 and details are discussed in Appendix D. These results confirm that all the variables are integrated of order one, denoted by $I(1)$, suggesting that first-differenced variables should be used in the following analysis.

5.2 An SUR Model of HE Demand

Clearly one cannot really study the demand for HE without examining the determinants of school staying on rates. In line with demographic constraints, university entrance rate can only rise if staying on rate rises and then qualified leaver rate increases. To do this we use the Seemingly Unrelated Regressions (SUR) model proposed by Zellner (1962) to estimate a system of equations of the post-16 staying on rate (S), the qualified leaver rate (Q), and the university entrance rate (UE). The SUR model permits contemporaneous cross-equation error correlation, and the equations are "seemingly unrelated" in the sense that they are related only through the error terms. Such a framework allows us to estimate multiple equations simultaneously while accounting for the correlated errors due to the fact that the models involve the same observations, resulting in efficient estimates of the coefficients and standard errors.

We include in the SUR model the expected gain from a university degree, namely the internal rate of return to undertaking a graduate job (IRR), along with the consumption value of education measured by the level of real consumption expenditure per head of the population (C). The internal rate of return with one-year lag (IRR_{t-1}) is included in the university entrance equation, while C enters all three equations of S, Q, and UE.

In addition, the impact of labor market conditions is represented by adult unemployment or youth unemployment, with a one-year lag (AU_{t-1} or YU_{t-1}) in the S equation, and the graduate unemployment with a one-year lag (GU_{t-1}) enters both of the Q and UE equations. We also measure the impact of average academic attainment ($GCSE$) in the S equation, staying on rate with a two-year lag (S_{t-2}) in the Q equation, and Q in the UE equation.

Also included in the UE equation is the variable relating to student finance policies, the net college cost ($COST$) or the net liquidity ($LIQUIDITY$). Accordingly, we have two specifications for our estimation using $COST$ (model 1) and $LIQUIDITY$ (model 2). For example, for model 1 we have a set of three equations of the following form, for males and females respectively:

$$\begin{aligned}
\Delta \ln S_t &= \alpha_{0,j} + \alpha_{1,j}\Delta \ln GCSE_t + \alpha_{2,j}\Delta \ln U_{t-1} + \alpha_{3,j}\Delta \ln C_t + \mu_t && (4)\\
\Delta \ln Q_t &= \beta_{0,j} + \beta_{1,j}\Delta \ln GU_{t-1} + \beta_{2,j}\Delta \ln C_t + \beta_{3,j}\Delta \ln S_{t-2} + \upsilon_t && (5)\\
\Delta \ln UE_t &= \gamma_{0,j} + \gamma_{1,j}\Delta \ln GU_{t-1} + \gamma_{2,j}\Delta \ln C_t + \gamma_{3,j}\Delta \ln IRR_{t-1} \\
&\quad + \gamma_{4,j}\Delta COST_t + \gamma_{5,j}\Delta \ln Q_t + \varepsilon_t, && (6)
\end{aligned}$$

where j indicates regimes (determined by structural breaks points that are exogenously detected), and the error terms μ_t, υ_t and ε_t are assumed to be correlated across equations. U_{t-1} in the S equation stands for the unemployment rate, which is adult unemployment (AU_{t-1}) or youth unemployment (YU_{t-1}) in two separate specifications of model 1. In model 2, $\Delta COST_t$ is replaced with $\Delta \ln(LIQUIDITY_t)$. Again, we include adult unemployment (AU_{t-1}) or youth unemployment (YU_{t-1}) in S equation for two separate specifications of model 2.

Two features of this model should be noted. Firstly, as will be explained in Section 5.3, the methodology of estimating structural changes rules out unit root regressors. Since we are constrained to model in first differences of the variables (due to the fact that all our variables are $I(1)$ in their level form), we are inevitably modeling the short-run relationship between our educational demand variables and their determinants. Secondly, in the specifications of our equations we are constrained by the logical recursive time structure of the university process. Specifically, since GCSE's, which determine S, are sat two years before 'A' levels, this means that S_{t-2} is the appropriate regressor in equation (5). Likewise 'A' levels are sat in the same year that university entrance takes place, so Q_t (unlagged) is the appropriate form in equation (6).[28] Also since each year in the time-series data relates to a separate cohort of 18-year-olds, there is little scope for any dynamic determinants in the specification. For these reasons, we do not employ an error correction model (by including lagged dependent variables in the models). Therefore more flexible dynamic modeling is precluded. We realize that this may be considered a shortcoming of model specification; but given that our main interest is in the short-run effect of average net college cost on UE, we think this model captures the focus of this paper.

Also worth mentioning is how we can interpret the coefficients in equations (4)-(6). As the unit root test results suggest, all the variables in these equations are $I(1)$. For a non-stationary time series, taking natural logarithms helps to stabilize the variance, while differencing helps to stabilize the mean. Therefore, we use first-differenced variables in the natural logarithm form, except $COST_t$ for which we do not take logs given its negative values in earlier years. Although the specification is different from that of a normal linear regression, the sign of an estimated parameter is still straightforward to interpret. Briefly, it reflects how a unit *change in the change* of an explanatory variable resulting in the *change in the change* of the dependent variable. The details are explained in Appendix E. For simplicity, the comments on the regression results in the following analyses will be phrased in the way we do for a "level-level" regression.

5.3 Structural Changes in a System of Regressions

We now discuss the structural changes in the model. Our multivariate analysis builds upon methodological developments of testing and estimation in the context of structural

[28] In our data, Q_t and UE_t correspond to the same calendar year. Q_t relates to the end of the application cycle of academic year t-1 to t, while UE_t measures the university entry in September of year t.

changes. A "structural change" is defined as an abrupt change in the structure of the modeled relation, with statistically significant and lasting shifts in the parameters of the conditional mean, the variance of the error term, or both. In a pure structural-change model, the structural change could occur to all coefficients. In a partial structural-change model, only part of the coefficients vary across regimes.

To estimate multiple structural changes simultaneously in a system of regressions, Qu and Perron (2007) provide a general framework that permits various complex models including SUR. Using their method, we regress the three-equation SUR model in the form of

$$y_t = (I \otimes z_t')S\beta_j + u_t, \tag{7}$$

where the subscript t indexes a temporal observation ($t = 1, ..., T$) and the subscript j represents a regime, $j = 1, ..., m + 1$. m is the total number of structural changes in the system and $m \leq M$, the pre-specified maximum number of breaks. y_t denotes an n-vector of dependent variables representing the long-term trend of participation rates (in our model the dependent variables are S, Q and UE, and therefore $n = 3$), I an $n \times n$ identity matrix, $z_t = (z_{1t}, ..., z_{qt})'$ a q-vector that includes the regressors from all equations, S a selection matrix that specifies which regressors in z_t enter in each equation, β_j a vector of estimated coefficients in the j th regime $T_{j-1} + 1 \leq t \leq T_j$. The error term u_t has mean 0 and covariance matrix Σ_j for the jth regime.

By assumption, Qu and Perron (2007) rule out unit root regressors. Since our unit root tests show that almost all of the variables are $I(1)$, the first-differences of the variables are used in the following model settings to ensure all the regressors are stationary, i.e. $I(0)$. In addition, Qu and Perron's results are asymptotic in nature, and as such we must acknowledge that with our relatively small sample size this is a clear limitation of our analysis.

We then use the procedure suggested by Qu and Perron to determine the presence, the number, and the timing of structural changes in the regression coefficients.[29] The procedure applies a so-called "double maximum" test of the null of no breaks against

[29] Qu and Perron's tests allow for changes occurring in the coefficients of the conditional mean (pure structural change model in the conditional mean), or changes occurring in the variance of the error term (pure structural change model in the covariance matrix), or changes occurring simultaneously in both (complete pure structural change model). Our analysis focuses on the first case.

the alternative hypothesis that an unknown number (m) of breaks occurs, where m is no larger than a given upper bound M, i.e. $m \leq M$ (Bai and Perron, 1998; Casini and Perron, 2019). If the double maximum test rejects the null of no breaks, a sequential F-type test, based on the estimates of the break dates obtained from a global maximization of the likelihood function, is then performed to test the null of l breaks against the possibility of $l + 1$ breaks and determine the number of breaks and their locations. The procedure conducts a one-break test for each of the $l + 1$ segments defined by the partition and adds one break each time the test is significant.[30] Throughout the procedure, a trimming value is pre-specified to impose a minimum length for each regime.[31] With the estimated break points, we then define the break dates in the SUR model and estimate intercept and trend coefficients in our models.[32]

Remark. In such a framework of an SUR model with structural breaks, we are inevitably constrained to impose the same structural break point across all the three equations. This might not be a realistic setup in that different policies usually affect different margins of education. However, this is a proper estimation methodology to address the main questions that our paper focuses on, given that the relations between the three rates are logically interconnected and ordered recursively. That is, the GCSE performance could vary with the staying on rate, and the changes in these rates could lead to a change in the university entrance rate. As such, the procedure for estimating a system of three equations allows us to detect the crucial structural changes underlying these interconnected relations, and thus is the approach to be taken in the following analysis.

[30] For details the reader is referred to Bai and Perron (1998, 2003), Perron (2005), Qu and Perron (2007), and Casini and Perron (2019).

[31] With a minimal length of the regime specified, some potentially important break points might not be observed, especially for the later years when substantial HE funding reforms have occurred frequently. This could be inherently problematic for our analysis. However, as we will explain in detail in Section 6.1, the procedure described above in fact provides an efficient way of evaluating the policy changes over the span of six decades.

[32] The tests were performed using the GAUSS code provided by Qu and Perron. Then we used STATA to do the inference conditioning on the estimated break dates and fit the model.

6 Results and Policy Simulations

In this section, we report the main results. The system to be analyzed consists of stochastic variables as discussed in Section 4. We estimate models with net college cost or net liquidity included in the UE equation. Tables 1 and 2 report the results, where we control for adult unemployment (AU) in the S equation (specification (a)). Tables F4 and F5 in Appendix F report the results with a similar setting, where we replace AU with youth unemployment (YU) in the S equation (specification (b)).

In what follows, we first show the estimated structural break points. We then discuss the main regression results and provide robustness checks. Finally, we present a policy simulation based on the regression results.

6.1 Structural Break Points

We first focus on Table 1 where $COST$ enters the UE equation. Our starting point is to discuss the years when major structural breaks occurred in the system of the three equations simultaneously. These are reported in the first column of Table 1. Along with the structural break points, we report the 95% critical intervals in the brackets as estimated by Qu and Perron (2007). As we can see in the upper panel, for males the break points are 1975 and 1993, whereas in the lower panel relating to females, the estimated break points are 1976 and 1998. Most of the confidence intervals are relatively loose (four years or longer), indicative of gradual changes over a longer time period rather than abrupt structural shifts in these cases.

The first structural break took place in 1975 or 1976, following the raising of school leaving age in 1972 which could have caused a structural shift in S, and hence might also have affected Q and UE. On the other hand, there seems to be a gender difference in the second structural break.

Table 1: Structural Break Test and Estimation (1958-2018)
Model 1(a)*: Net College Cost

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Male		0.029	0.531	0.162***	-1.057	0.007	0.087*	0.779	0.302	0.023	0.164***	-0.958	-0.540***	0.028	0.367*
	1975	(0.020)	(0.346)	(0.053)	(0.642)	(0.032)	(0.052)	(0.684)	(0.431)	(0.020)	(0.055)	(0.829)	(0.163)	(0.048)	(0.221)
	[1970 1980]	0.013	0.826***	0.088*	-0.284	0.017	0.049	0.057	0.213	0.002	-0.044	-0.098	-0.011	-0.049	1.166***
	1993	(0.018)	(0.265)	(0.049)	(0.405)	(0.020)	(0.049)	(0.500)	(0.153)	(0.019)	(0.044)	(0.469)	(0.206)	(0.054)	(0.251)
	[1990 1996]	0.011	-0.085	0.013	-0.168	0.003	-0.017	0.440	0.903**	0.013	-0.107	0.305	-0.067	-0.052**	0.279
		(0.010)	(0.147)	(0.061)	(0.525)	(0.013)	(0.074)	(0.604)	(0.457)	(0.011)	(0.073)	(0.543)	(0.120)	(0.025)	(0.213)
	N	61				61				61					
	R^2	0.495				0.349				0.566					
	F-Stat	4.957				2.727				4.407					
	Prob >F	0.000				0.002				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Female		0.039**	0.362	0.161***	-0.672	0.014	0.142***	0.944	0.524**	0.047**	0.120**	0.360	-0.417**	-0.041	0.071
	1976	(0.018)	(0.266)	(0.040)	(0.557)	(0.023)	(0.043)	(0.657)	(0.213)	(0.018)	(0.046)	(0.575)	(0.167)	(0.036)	(0.165)
	[1974 1978]	0.014	0.457**	-0.039	-0.273	0.043**	-0.070	-0.434	0.488**	0.017	-0.046	0.069	0.158	-0.076***	0.816***
	1998	(0.015)	(0.182)	(0.038)	(0.350)	(0.017)	(0.055)	(0.465)	(0.198)	(0.017)	(0.049)	(0.413)	(0.184)	(0.025)	(0.167)
	[1995 2001]	0.009	-0.046	0.041	0.423	0.012	-0.011	-0.091	0.524	0.020*	-0.251***	0.342	-0.152	-0.025	0.294
		(0.009)	(0.154)	(0.060)	(0.587)	(0.015)	(0.102)	(0.660)	(1.015)	(0.011)	(0.091)	(0.562)	(0.141)	(0.027)	(0.308)
	N	61				61				61					
	R^2	0.500				0.558				0.719					
	F-Stat	5.084				6.426				8.540					
	Prob >F	0.000				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

*Note: Adult unemployment (AU) is used in S equation.

Table 2: Structural Break Test and Estimation (1958-2018)
Model 2(a)*: Net Liquidity

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Male		0.029	0.530	0.163***	-1.060	0.007	0.087*	0.778	0.298	0.022	0.163***	-0.946	-0.535***	-0.109	0.372
	1975	(0.020)	(0.346)	(0.053)	(0.642)	(0.032)	(0.052)	(0.684)	(0.431)	(0.021)	(0.057)	(0.850)	(0.166)	(0.202)	(0.232)
	[1971 1979]	0.014	0.826***	0.087*	-0.284	0.017	0.049	0.057	0.213	-0.000	-0.050	-0.017	0.031	0.169	1.083***
	1993	(0.018)	(0.265)	(0.049)	(0.405)	(0.020)	(0.049)	(0.500)	(0.153)	(0.019)	(0.046)	(0.478)	(0.218)	(0.152)	(0.282)
	[1990 1996]	0.011	-0.081	0.012	-0.170	0.003	-0.017	0.441	0.904**	0.009	-0.069	-0.006	-0.122	0.028	0.165
		(0.010)	(0.147)	(0.061)	(0.525)	(0.013)	(0.074)	(0.604)	(0.457)	(0.012)	(0.074)	(0.539)	(0.121)	(0.067)	(0.213)
	N	61				61				61					
	R^2	0.495				0.349				0.541					
	F-Stat	4.955				2.728				4.003					
	Prob >F	0.000				0.002				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Female		0.036	0.347	0.145**	-0.559	0.009	0.139***	0.988	0.598	0.047***	0.131***	-0.371	-1.804***	0.029	0.156
	1975	(0.024)	(0.320)	(0.060)	(0.677)	(0.038)	(0.047)	(0.721)	(0.511)	(0.017)	(0.044)	(0.601)	(0.568)	(0.141)	(0.155)
	[1973 1977]	0.022	0.354*	0.024	-0.299	0.050***	-0.033	-0.420	0.305*	0.014	-0.057	0.098	0.086	0.249***	0.745***
	1998	(0.016)	(0.196)	(0.036)	(0.382)	(0.017)	(0.049)	(0.474)	(0.156)	(0.016)	(0.045)	(0.376)	(0.118)	(0.068)	(0.160)
	[1995 2001]	0.009	-0.048	0.040	0.415	0.012	-0.014	-0.096	0.516	0.022**	-0.185**	0.434	-0.269*	-0.103	0.262
		(0.010)	(0.168)	(0.065)	(0.640)	(0.016)	(0.104)	(0.673)	(1.032)	(0.010)	(0.088)	(0.534)	(0.143)	(0.075)	(0.282)
	N	61				61				61					
	R^2	0.402				0.539				0.753					
	F-Stat	3.368				6.030				10.270					
	Prob >F	0.000				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

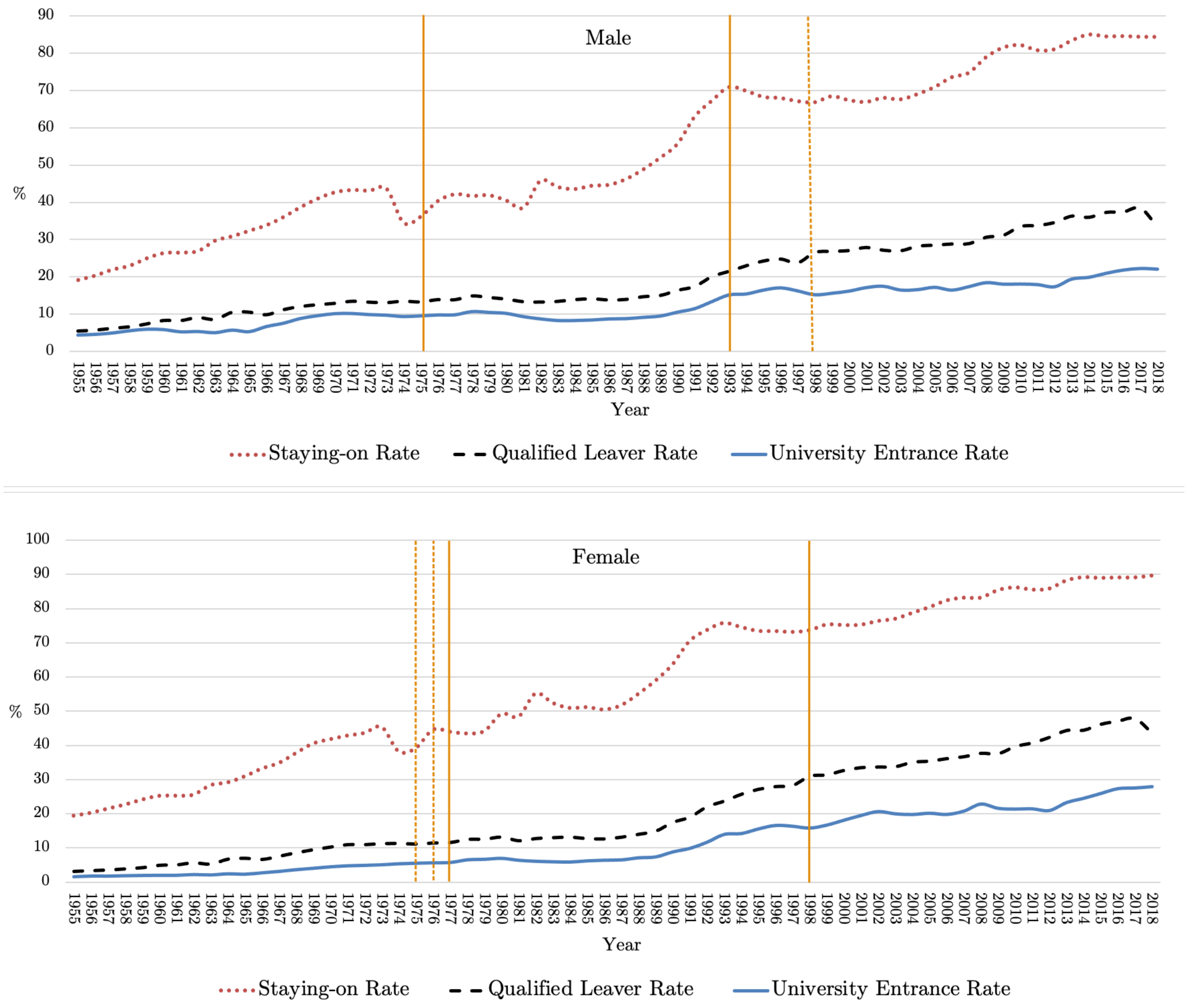
*Note: Adult unemployment (AU) is used in S equation.

For the male subgroup, the break point is estimated to be 1993. This is concurrent with the Further and Higher Education Act 1992, under which more education institutions - including 35 former polytechnics - were granted university status and degree awarding power. Subsequently most of these HEIs, commonly referred to as "post-1992" universities, started to offer a broader range of degree subjects, leading to the most recent round of expansion in the UK's HE sector in the early 1990s. Furthermore, as our UE data indicates, these years also saw a jump in male students' university entrance rate and hence a widening disparity between men and women's HE enrollment. The break point being detected for the male subgroup at 1993 could be partly related with the overrepresentation of male students in polytechnics in history (see, e.g., Egerton and Halsey, 1993). Another possible explanation is that many post-1992 universities were formerly polytechnics and mostly delivered vocational degree courses. While students in the traditional 'A' level route were more likely to progress to pre-1992 HEIs (Hoelscher et al., 2008), the "new" post-1992 institutions opened up more education opportunities for students with non-traditional qualifications, especially for boys who were more represented in candidates with vocational backgrounds. Consequently, there was a dramatic rise in male students' university entrance, which translates into a significant break point for the male subgroup in our model.

A different break point was observed for the female subgroup in 1998, five years after the break point for the male subgroup. The timing of this structural break coincided with one of the most important funding reforms over the past few decades: the introduction of up-front tuition fees and the expansion of student loans in 1998. This could be partly due to the fact that women's lifetime earnings are in general lower than men's, and thus they typically benefit more from the HE funding reforms especially the student loan policies. As such, tuition fees are a less deterrent factor in affecting women's university application. In fact, as we can see in the lower panel of Figure A.2, women's university entrance rate exceeded that for men around 1998 for the first time, meaning a crucial structural change for females.

Table 2 - where net liquidity enters the UE equation - presents very similar break points. Estimation results with the youth unemployment included in the S equation also report similar break points (see Tables F4 and F5 in Appendix F). One exception is Table F5, where the second break points for male and female subgroups are both estimated to be 1998.

Figure 5: Estimated Structural Breaks



All these structural break points are depicted in Figure 5. Overall, the raising of school leaving age in 1975, the creation of post-1992 universities in 1992, and the 1998 funding reform appear to have dominant impacts on the structural shifts in post-compulsory education participation. The tests, however, haven't indicated any break point associated with some recent important reforms such as the 2006 reform or the 2012 reform. In fact, this is due to the methodology used and the fact that these reforms took place in relatively recent years. As explained in Section 5.3, the trimming value is an essential parameter that must be pre-specified in the structural break tests. There is a trade-off when deciding an appropriate minimum length for the regime. If we set a minimum length that is too large, we might miss some potential break points; whereas an overly short minimum length will probably lead to misleadingly detecting a short-run adjustment as a structural change. In practice, we use a trial-and-error procedure to decide a minimum length, which is about one-quarter of the sample size. With the trimming value specified, the procedure can inevitably overlook some potentially important break points that might have occurred lately. Nevertheless, the tests provide an effective way to detect the major break points; whereas we need to keep in mind that some potential break points might also exist but are just undetectable due to the relatively short time period of our time-series data.

6.2 Regression Results

Tables 1 and 2 present our main regression results. These results are based on three time intervals that are split by the estimated structural break points as discussed in the preceding section.

The regression results suggest that the post-16 staying on rate is primarily driven by the average academic attainment measured by exam results in GCSE (or equivalent prior to 1988). This effect is positive, statistically significant, and larger around the replacement of O-levels with GCSE in 1988. The finding is supported by the evidence in existing research that the improvement in GCSE attainment levels since the late 1980s has contributed greatly to the rapid growth in participation rates (McIntosh, 2001; McVicar and Rice, 2001). In turn, the staying on rate is found to exert a positive effect on the qualified leaver rate, and the latter plays a positive role in determining the movements of university entrance rate. The results are consistent with the evidence provided by Pissarides (1982).

Overall youth unemployment and adult unemployment are positively associated with the staying on rate. The youth unemployment rate in the equation represents the probability of unemployment for early school leavers, so an increase in it means lower opportunity costs for staying on in school, resulting in a higher demand for education, in line with Adamopoulou and Tanzi (2017)'s findings. On the other hand, adult unemployment seems to exert a significantly positive effect on participation in post-16 education, but mainly during the first and second time intervals spanning from the late 1950s to the late 1990s. Adult unemployment is usually associated with family financial status and therefore better approximates youths' current income constraint. In general, high adult unemployment indicates a deterioration in family financial conditions, which could lead to lower demand for education. Yet, this negative impact can be outweighed by young people and their parents' expectations for the gains from a college degree if the expectations are sufficiently high (Tumino and Taylor, 2015).

The interpretation of the impact of graduate unemployment seems unclear in the Q and UE equations. The graduate unemployment rate measures the percentage of unemployment among graduates who obtained undergraduate qualifications through full-time study. In most cases, graduate unemployment exerts a significant and positive impact on both of the qualified leaver rate and the university entrance rate for the pre-1980 period. For the female cohort, graduate unemployment appears to be negatively correlated with the university entrance rate in the most recent time interval, indicating that the expectation of graduates' employability did not play a consistent role in determining HE participation.

The effect of the average consumption expenditure is insignificant in most of the specifications. Strikingly, the internal rate of return to undertaking a graduate job (IRR) appears to be negatively correlated with the demand for HE, especially in the first time interval (before the mid-1970s), with statistically significant coefficients. One major concern arises from the IRR data itself. As discussed in Appendix C, our own IRR is estimated on the basis of NES and LFS. And the data only goes back to 1975 because earlier information is unavailable from these surveys. For the pre-1975 data, we refer to Wilson's work (Wilson, 1980, 1983, and 1985), which might have resulted in an inconsistency in the IRR data. To investigate the impact of IRR further and also provide checks on the robustness of our main results, it is necessary to restrict the sample to years from 1975. Details are provided in Section 6.3.1.

Turning now to the variables of particular interest in our analysis, we find that the estimated coefficients of net college cost do lend credence to the view that the less generous support arrangements can deter HE participation. As shown in Tables 1 and F4, among the time intervals split by the estimated break dates, the latter two intervals exhibit negative effects of college costs on university entrance. These effects are statistically significant for boys in the third time interval (from 1993 to 2018), and for girls in the second interval (from 1976 to 1998). This indicates that the responses varied by gender to policy changes related to different elements of HE costs. A potential reason is that, compared with their male counterparts, female students might be more sensitive to changes in student grants in earlier years; by contrast, they are likely less responsive to the reforms of tuition fees and student loans which took place over the post-1998 period. We now discuss the results in greater detail and provide further explanations.

A notable finding in Table 1 is that the negative effect of college costs on girls' desire for HE diminishes substantially over the past four decades. The influence for girls' HE entrance appears statistically significant and quantitatively larger than that for boys in the second interval of time (from the mid-1970s to the 1990s), which is concurrent with the era of free college coupled with more generous student supports. The *negative* college cost as in our time-series data during this time period literally represents the *positive* value of student grants, effectively meaning that grants reduce the cost of attending university (Dynarski, 2003). As such, the results suggest that student grants encourage HE enrollments, and the impact is larger in magnitude for female students. This is consistent with the evidence in the US context provided by McPherson and Shapiro (1991), who demonstrate that HE enrollment rates were higher for women than for men over the 1974-1984 period, after the introduction of a need-based federal grant program. One possibility is that female students tend to have stronger preferences for education (e.g., Belfield et al., 2020). Another potential reason is that the female labor force participation rate was lower at the time. Therefore when it comes to HE participation decisions, women were less propelled by economic returns to a college degree; rather, they could care more about college costs which could be partially offset by student grants. Consequently, student grants might be a more prominent determinant of their educational investment for this time period.

The third time interval features the switch from the zero-fee regime to a high-fee, high-loan system. Looking at this period of time, the results show that the impact of net college cost for boys slightly increases in magnitude over time; and the size of the adverse effect is substantially larger for boys than for girls. On the one hand, girls might be less affected by the funding reforms over the past two decades, despite the continuously rising cost of HE education. The mechanism behind this is that, in general, women benefit more than men from the new HE funding arrangements because their lifetime repayments of loans are expected to be lower due to their lower income profiles over lifetime (Crawford and Jin, 2014). By contrast, men tend to work for more years over their lifetime and usually get paid higher wages. As such, their incomes are more likely to be above the repayment threshold for a longer period of time, resulting in higher loan repayments. Consequently, men could be more sensitive to the rises in tuition fees (and hence student loans).

On the other hand, investment in HE involves costs not only in the form of direct costs (including tuition fees and cost of living) but also in terms of opportunity costs, that is, forgone earnings of going to university instead of working. This opportunity cost is usually proxied by unskilled wages of high school graduates (e.g., Dynarski, 2003). In general, men have wider access to high-paying occupations that do not require a college degree, thus male students' opportunity costs are generally higher than their female counterparts. On top of that, fee loans have increased dramatically over years, and given men's higher lifetime earnings, they typically anticipate higher, income-driven lifetime loan repayments.[33] Consequently, they are more inclined to expect higher total costs of schooling. Moreover, as our own estimates of internal rate of return suggest, overall men's economic returns to college education are persistently lower than women's, which is illustrated in Figure C.1. Taken together, we could expect that male students are more likely to be deterred from participating in HE if their expected gains from university study are outweighed by their total educational costs.

The evidence appears mixed in terms of students' net liquidity that's available during their HE studies. The effect is found to vary by gender in the first time interval, prior to the mid-1970s. Whereas more consistent evidence is observed in the second time interval, when the HE finance arrangements were more generous to students before the 1998 reform took place. During this time interval, most of the coefficients of net liquidity are positive and statistically significant, consistent with the expectations that HE enrollment increases with students' liquidity that's available during their HE studies. By contrast, the demand for HE appears insensitive to changes in students' net liquidity over the past two decades, despite the steady rise in the liquidity after 2006. As can be seen in Figure 4, clearly there was a dip in the net liquidity alongside the introduction of up-front fees, while this decrease was counteracted by a surge around 2006 as a result of the introduction of variable fees and tuition fee loans. Considering these substantial changes occurred over a relatively short time (only twelve years in our sample of data), the estimated impact may not represent a long-run response to policy

[33]For instance, Bachan (2014) finds that male students expect themselves to be more indebted than female students.

changes over the post-1998 era. We will further discuss the impact of net liquidity in the following section.

6.3 Robustness Checks

6.3.1 From 1975 to 2015

In this section, we discuss the results for a shorter time period from 1975 to 2015, as a robustness check of the estimated coefficients of net college costs and net liquidity as previously discussed. On the one hand, as discussed in the preceding section, our data of variable IRR is subject to potential inconsistency because we refer to Wilson's earlier work (Wilson, 1980, 1983, and 1985) for the pre-1975 data. On the other hand, as can be seen in Figure 1, there is a decline in the qualified leaver rate towards the end of our sample period of time. This is because of a few changes in both statistical methods and government policies in England since 2016, including the implementation of a new "16-18 school and college accountability system" in 2016 and the introduction of reformed GCSE in 2017. As such, the official statistics since 2016 relating to 'A' level and other 16-18 examination results are not directly comparable to those of earlier years. This could lead to inconsistent data on qualified leavers for the years from 2016 to 2018.

Tables G6-G9 in Appendix G report the regression results for the shorter time period from 1975 to 2015. As indicated in the results, the coefficients of net college cost and students' liquidity are broadly comparable to those of the main results in Section 6.2. This suggests that our understanding of the effect of HE finance policy changes is convincing. Furthermore, in most of the time intervals, net college cost appears to exert significantly negative impacts on university entrance, consistent with the expectations that higher college costs deter HE participation.

Notably, the effect of students' net liquidity has varied over time and most of the coefficients are statistically significant. University entrance rate seems to increase with net liquidity in earlier years, before up-front fees were introduced to the HE system in 1998. Afterward, it appears to be *negatively* correlated with net liquidity. However, as discussed in Section 5.2 and Appendix E, due to the special specification of our models, the coefficient in the models should be interpreted as a unit *change in the change* of an independent variable resulting in the *change in the change* of the dependent variable. A negative sign here does not necessarily conclude that an increase in liquidity will lead to a decrease in university entrance. Rather, it could suggest that the positive effect has *flattened out* in these recent years.

As a matter of fact, a calculation based on the negative coefficients (-0.072 for boys and -0.151 for girls in Table G8) indicates that a £100 rise in net liquidity would result in an increase in university entrance rate by 0.419 percentage points for males and 0.157 percentage points for females. Yet the negative coefficient implies that the increasing trend in university entrance might have slowed down in recent years, despite that students' liquidity has been increasing since 2006. The underlying reason could be that, as Murphy et al. (2019) conclude, students' liquidity is not adequate to cover either the direct costs of living or the opportunity costs of foregone earnings under the current student finance scheme.

Overall the effect of IRR on university entrance remains mixed. Take Table G9, for example - the result indicates that university entrance rate is positively correlated with IRR in the earliest time interval (from 1975 to 1988); whereas the opposite is the case for the most recent interval (from 2002 to 2015).

The results for the time interval from 1975 to 1988 are consistent with what the standard models of human capital investment predict: the wage premium associated with a college degree strengthens individuals' intention to invest in schooling. As shown in Figure C.1, there was a remarkable rising trend in the IRR during the 1980s, as a result of a growing demand for high-skilled workers in the labor force. This widening wage gap between graduates and non-graduates has been found to be a dominant factor to boost HE growth over this time period (e.g., Blanden and Machin, 2004).

However, when it comes to human capital investments, the consideration of educational benefits is not affected solely by expected returns to schooling; rather, the interplay between educational returns and other factors to a great extent matters in educational decisions. First, returns to HE are largely uncertain at the time of decision-making due to unpredictable factors such as future earnings and employment prospects. Besides, as reflected in Figure C.1, the fluctuations in IRR are particularly evident over the most recent time interval. Such variance over time in returns to university education can also contribute to the uncertainties about educational benefits. For risk-averse individuals, these uncertainties could play an important role in one's cost-benefit trade-off, especially for risk-averse individuals. As Glocker and Storck (2014) point out, university education is not necessarily a better route than other types of education when students take such uncertainties into consideration and evaluate returns to schooling against the associated risks.

Second, the IRR data is calculated over all HE qualifications and degree subjects. Whereas returns to education can be differentiated by educational levels as well as fields of study, which our analysis at the aggregate level does not address. In fact, the income-contingent nature of the student loan repayment system will possibly affect potential HE students' choices of college majors. On the other hand, faced with the uncertainty of realizing educational benefits, risk-averse individuals may opt for degrees associated with lower variance in earnings. In this sense, demand for HE can be prominently determined by degree-specific returns (and risks) rather than the average rate of returns.

Third, even in the presence of rising returns to schooling, educational decisions can be influenced by loan aversion, which has been shown to be commonplace among young people (see, e.g., Bates et al., 2009; Field, 2009). Individuals who are unwilling to borrow for college education are more likely to be put off by the increasing tuition fees and hence fee loans. In the UK, over the most recent time interval from 2002 to 2015, students have become largely dependent on student loans to fund their university study. And this great reliance implies that some debt-averse individuals could be deterred from attending university, regardless of the potentially positive returns to HE in the long run.

6.3.2 Structural Breaks Imposed at 1998, 2006, 2012

To probe the robustness of our results, we also re-estimate the main regressions of models 1(a), 2(a), 1(b), and 2(b) (corresponding to Tables 1, 2, F4, and F5 respectively), with the structural break points imposed at years 1998, 2006, 2012, which are in line with the three major reforms that took place in UK's HE finance policies over the past few decades. Table G10 in Appendix G reports the coefficients of net college cost or net liquidity in the UE equation, over the entire period of 1958 to 2018.

Overall, the results are consistent with our previous findings that demand for HE decreases with the net college cost and increases with students' liquidity that's available during their HE studies. Although the signs of the coefficients are broadly comparable with those in the main results, most of the effects appear insignificant in the latter three time intervals, that is, over the years after 1998. This could be due to the small sample size for the post-1998 period.

6.4 Policy Simulation

The aggregate statistics of university entrance rate have exhibited a continuous upward trend so far. However, given that the estimated coefficients on $\Delta COST$ are negative, if the tuition fees continue to rise, the net college cost might be increased to such a high level that it would deter HE enrollment. To illustrate this, based on the estimated results, we present a policy simulation and explore the consequences of a rise in net college cost due to increased tuition fees (represented by the NPV of graduate loan repayment). Specifically, we estimate the effect of an increase in the NPV of loan repayment by £1,000, *ceteris paribus*.

Remark. Here, we define a unit (i.e. a £1,000) change in the college cost in order to benchmark the policy simulation against existing research. For instance, in evaluating the impacts of funding reforms, Kane (1994), Dynarski(2003), and Dearden et al. (2014) examine the effect of a \$1,000 or £1,000 change in student supports. It should also be noted that, for ease of comparison between our results and those in other studies, an ideal measure would be an increase in tuition fees by £1,000. However, this is not feasible in this paper as our main estimation uses the NPV of graduate loan repayment instead of sticker price, while the simulated data of NPV repayment accompanying a £1,000 rise in fees is currently unavailable. Only updated data on this would enable us to evaluate the effect of a £1,000 rise in tuition fees, and future research is needed to address this point.

Starting from the coefficient of $\Delta COST$, we have

$$\gamma_4 = \frac{d(\Delta \ln UE_t)}{d(\Delta COST_t)} \tag{8}$$

From equation (8) the following equation is derived, reflecting the change in $\ln UE_t$ from 2018 to 2019 is

$$\Delta \ln UE_{2019} = \gamma_4 d(\Delta COST_{2019}) + \Delta \ln UE_{2018} \tag{9}$$

where $\Delta COST_{2019}$ is the increase in the NPV of lifetime loan repayment. Based on equation (9) and the estimated γ_4 in Table 1 (-0.052 and -0.025 for boys and girls respectively), we can then predict the new university entrance rate with college costs rising, and compare it with the current university entrance rate UE_{2018}.[34] Under the

[34] As discussed in Section 6.1, because the sample size is relatively small whereas a minimum period

assumption that the NPV of loan repayment rises from the current level (as of year 2018) by £1,000, the calculation indicates that the university entrance rate would decrease by 1.37 and 0.37 percentage points for boys and girls respectively, relative to the current position of year 2018. This projection assumes that there have been no changes to grants and loans, and that the underlying regression results are valid for "out of sample" predictions. Such assumptions are only a first approximation to the scale of the effect of raising costs. The estimated decrease in girls' university entrance is comparable to Azmat and Simion (2021)'s finding that, as a result of either the 2006 reform or the 2012 reform, the overall enrollment decreases by 0.5 percentage points.

As another policy simulation to shed some light on the ongoing education policy debates, we examine the consequence of an increase in tuition fees by a hypothetical figure of £4,000 a year, and thus an increase in NPV of graduate loan repayments by approximately £2,903.[35] Following the same procedure described in the preceding simulation, the university entrance rate is now estimated to decrease more considerably, relative to the current position (academic year 2017/18), by 3.31 and 1.65 percentage points for males and females respectively.

We then proceed to compute elasticity of the university entrance rate with respect to the net college cost, also based on equation (8) and the coefficient estimates from Table 1. Our calculation suggests elasticity of -0.121 and -0.026 for boys and girls respectively. The estimated elasticity for boys is in line with Sá (2019)'s estimated elasticity of university applications regarding the 2012 reform, which is -0.11; while the elasticity is smaller in magnitude than her estimated elasticity of -0.36 with respect to the reforms over the past two decades.

The heterogeneity in elasticity by gender is consistent with our findings that over the post-1998 era, net college costs appear to exert a statistically significant and larger adverse impact of on men's demand for HE, compared with women. This could be partly

length must be pre-specified in the structural break tests, it is difficult to detect some potentially important break points that might have occurred in more recent years. Since the policy simulations being discussed draw upon the estimates in the last time interval, when interpreting these results, this data limitation should be kept in mind and more cautions need to be exercised. And further extension of the data set is needed to more carefully address these concerns.

[35]It is important to note that here the increase in NPV of graduate loan repayments is just a rough approximation based on the current data set and our own estimation. For a more precise prediction, we should refer to the simulated NPV repayment data when it becomes available.

related with women's lower lifetime earnings and thus lower expected loan repayments, meaning that they are less likely to be affected by the continuous rise in HE costs and thus less responsive to changes in student-funding policies. Another reason underlying the gender difference is the interplay between pecuniary returns to education and costs of schooling - direct and indirect - in making educational educations. According to our own time-series data of IRR, returns to college education overall appear to be lower for men than for women; whereas opportunity costs of forgone earnings (for going to university) are generally higher for male students. In the presence of higher opportunity costs of schooling, coupled with growing tuition fees or fee loans (and hence higher income-driven loan repayments for men) over the past two decades, male students may be less willing to invest in HE if the total costs overtake their expected future benefits. Therefore, men's demand for HE appears to be more sensitive to the variation in college costs over recent years.

7 Conclusion and Discussion

A central and controversial issue currently facing HE policymakers in any country is whether less generous student financial support arrangements have a negative effect on the demand for HE. Motivated by this subject of discussion, our paper examines the demand for HE in England and Wales over the past six decades. We set out to exploit the regime changes in HE funding to identify the causal impact of these changes on the demand for HE, using the procedures developed by Qu and Perron (2007) for determining system breaks in an SUR model.

Three main conclusions can be drawn from our results. First, various important factors are in play in determining participation in post-compulsory education, such as the average academic attainment measured by exam results in GCSE and the probability of employment for early school leavers (in the S equation), the post-16 staying on rate (in the Q equation), and the qualified leaver rate (in the UE equation).

A particular highlight of our analysis is the tests for structural break points, which suggest important changes in HE policies, especially the raising of school leaving age in 1972, the creation of post-1992 universities in 1992, and the introduction of tuition fees and income-contingent maintenance loans in 1998, did occur in line with significant structural shifts in the SUR model of post-compulsory education participation. These break points apply to a system of three equations with three outcome variables - post-16 staying on rate, qualified leaver rate, and university entrance rate - and thus reflect the structural changes in the interconnected relations of young people's three-stage schooling decisions. Realistically a policy change that initially targets one specific outcome will also lead to structural changes in the other outcomes. The raising of school leaving age effectively increased the proportion of the 16-year-old age group attending schools, accompanied by higher qualified leaver rate and university entrance rate in subsequent years. Under the circumstances that growth in male students' qualified leaver rate slowed down in the late 1980s, the new post-1992 universities actually opened up more education opportunities for males with vocational backgrounds, resulting in a substantial rise in their university entrance. In the face of HE funding reforms, not only prospective college students' incentives to attend university but also school leavers' educational decisions might be affected, and this impact could vary by gender. The interplay of all these influences should draw serious attention, and careful consideration of the context of the system is needed for thorough policy analyses.

Second, our study confirms existing evidence that higher college costs do deter HE participation, and throws up interesting findings that this adverse impact is larger in magnitude on young males than females. While the results for earlier years (from the mid-1970s to the 1990s) indicate that female students are more responsive to changes in student grants when it comes to HE participation decisions, for the post-1998 era, males appear to be more sensitive to the vastly increased tuition fees and hence fee loans.

The latter stark gender imbalance implies that nowadays debt aversion may be stronger among males under the current high-fee, high-loan HE system, partly because they generally expect themselves to face greater, income-driven loan repayments over lifetime. Another implication is that males typically perceive lower, uncertain economic returns to education. In fact, as far as the internal rate of return to HE is concerned, not only was its level continuously lower for men but also the fluctuation in it appeared more pronounced for men over the past two decades, which is reflected in Figure C.1. Apart from that, non-pecuniary factors, such as ability and tastes, might be the importance force behind the gender heterogeneity in HE participation. For one thing, as our time-series data reveals, female students have consistently outperformed males in both GCSE outcomes (since the 1980s) and 'A' level results (since 1990), indicative of a persistent gender gap in readiness for university education. In addition, we might imagine that males tend to have lower educational aspirations (see, e.g., Hillman and Robinson, 2018). Given all of these concerns, men and women are reasonably expected to have distinct incentives and make different HE decisions, which necessitates taking account of the gender heterogeneity and rethinking the associated mechanisms when evaluating the effects of HE funding reforms.

Third, our policy simulation suggests that if net college costs were increased by £1,000, the university entrance rate would decrease by 1.37 and 0.37 percentage points for boys and girls respectively, relative to the current position (the latest year in the sample, i.e. the 2017/18 academic year). Further, a rise in tuition fees by £4,000 would lead to a more considerable fall in the university entrance rate, also with a larger adverse impact on males than females. Similarly, elasticity of the university entrance rate with respect to the net college cost is found to be negative for both the male and female subgroups. Although the past years have seen no evident downward trend in HE participation despite a hike in fees, what we can infer from all the above results is that the detrimental impact of rising college costs on the demand for HE could be exacerbated if tuition fees were increased by a larger amount, coupled with the soaring real value of fees in the form of expected lifetime fee loan repayments.

UK's HE system is under intense financial pressure nowadays. The cap of domestic tuition fees has remained frozen at £9,250 for full-time undergraduate courses in England (£9,000 in Wales) since academic year 2016/17, without keeping pace of escalating inflation over recent years. In the face of rising deficit incurred for teaching domestic students, some universities have called for rises in the cap of tuition fees, or else they might opt to cut back on places not only for home students but also for some important STEM courses that are relatively costly to supply. However, policymakers should be fully aware of the potential long-run consequences of the soaring costs of HE and the trade-off between resource and equity. Were tuition fees further increased, potential college students, in particular those from poorer families with limited access to parental support, would expect themselves to take up more student fee loans to cover the cost of attendance. This may inhibit enrollments of these economically disadvantaged students, as they are especially prone to loan aversion (see, e.g., Callender and Jackson, 2005; Baum and Schwartz, 2015), which in turn may further impair social mobility.

On top of that, there might be a significant impact on some poorer and less selective institutions who recruit their students predominantly from the disadvantaged backgrounds. These effects could be all the more important given that a higher proportion of resources are allocated to those more selective institutions. According to the most recent UK Research and Innovation (UKRI) university funding publication (Research England Grant Allocations 2022/23, August 2022), those in the bottom quartile of all 130 institutions in England only received 2.83% of the total recurrent quality-related research (QR) and Higher Education Innovation Funding (HEIF) grants for the 2022/23 academic year. Under the circumstances that the level of tuition fees is to be further lifted, and if the demand for HE drops subsequently as predicted in our model, then the already large resourcing disparities between institutions will be exacerbated and may endanger the very existence of some of less well-established institutions. Moreover, it is quite likely that raising the tuition fees in the way we have explained could give rise to some issues in the equity of educational access to HE, as it is these less well-established universities which have a better track record in providing HE places to students from less wealthy parental backgrounds.

All in all, sharing the costs between the society and the individual participants in HE ought to be both efficient and equitable. Realistically any change to a system of HE funding that relied more on individual student fees could exclude many of the economically disadvantaged students from HE participation and endanger some of the less well-established institutions. And all these detrimental consequences warrant greater efforts in careful policy assessment and proactive policy-making.

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Appendix A Applicants to University

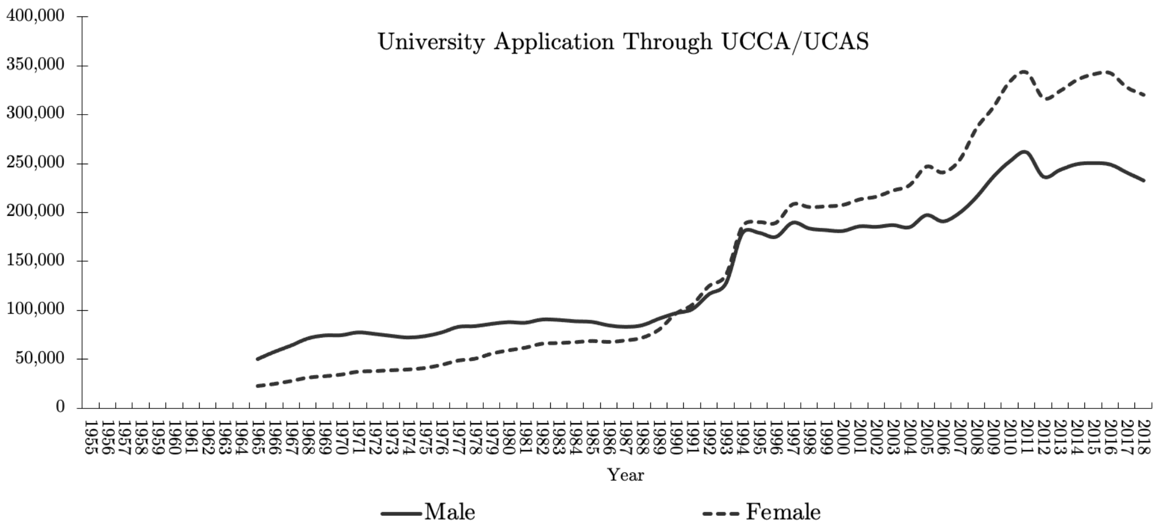
For completeness, we add a further set of figures in this appendix relating to trends in university applications. In examining these figures it should be remembered that up until 1993 prospective students could apply to polytechnics, universities, or both. Unfortunately, central data on polytechnic applications prior to 1993 do not exist. In addition, even if they did, we would not know the extent of double-counting (of students who applied to both types of institutions). In this appendix we provide data on the number of male and female applicants to university by year and the fraction of applicants who gain entrance respectively in Figures A.1 and A.2.

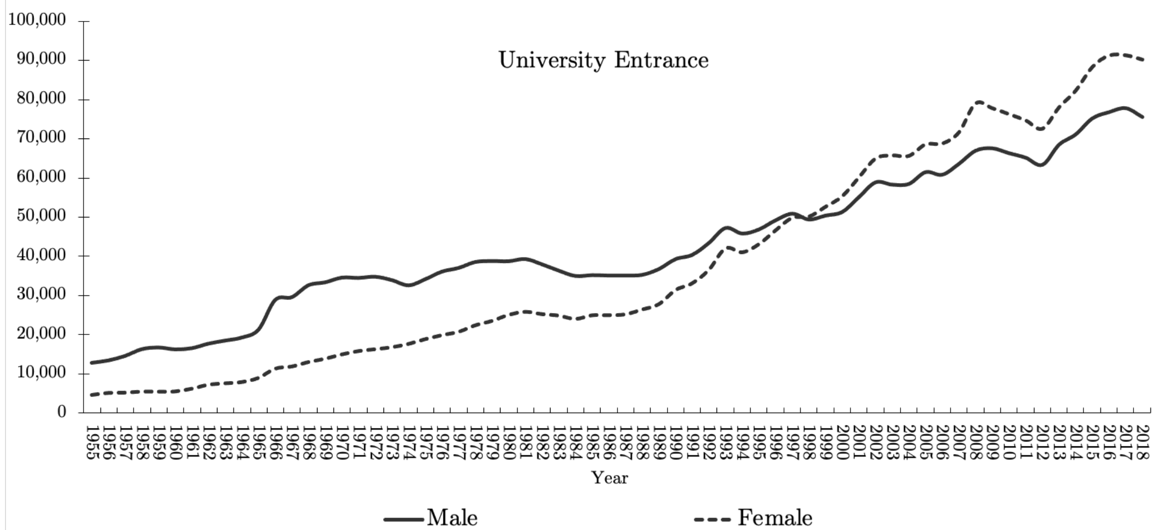
What we see from Figure A.1 is that, post 1994, between 75-80% of applicants get into university. This is approximately the fraction of any cohort who are qualified and wish to continue their studies. This substantiates the view that the Robbins principle of 1963 has broadly been upheld. This also conveniently establishes our point that supply of university places is, to all intents and purposes, unconstrained.

Looking further at the pre-1993 period, it is clear that the university sector took between 50-55% of applicants – where presumably the other 25-30% of applicants went to polytechnics. One clear "dip" in the data occurs in the 1982/83 period which coincided with the Thacher university cuts of 1981. Another dip in this fraction occurs in the 2011-2013 period, again concurrent with the cuts in higher education.

Figure A.1: Fraction of Applicants Who Gained Entrance to University (Home Students)

Figure A.2: University Application and University Entrance (Home Students)





Appendix B Unemployment Rate

Figure B.1: Youth Unemployment Rate

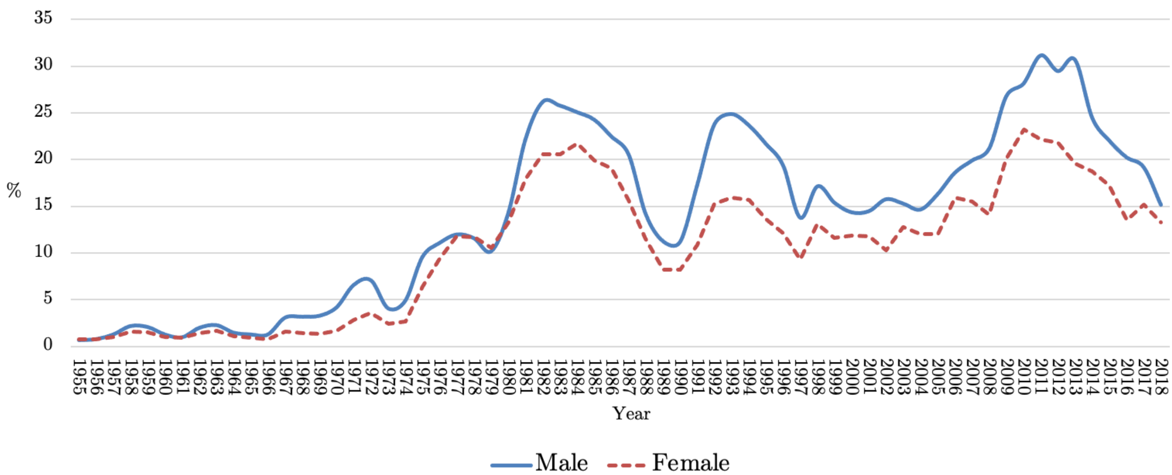


Figure B.2: Adult Unemployment Rate (ONS Series ID: MGSX)

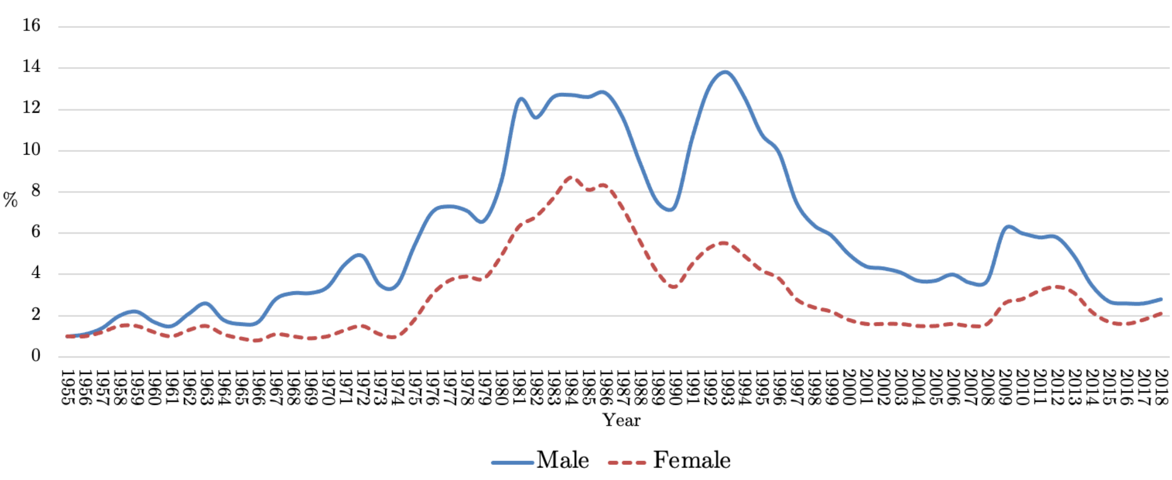


Figure B.3: Graduate Unemployment Rate

Appendix C Internal Rate of Return Calculation

We use LFS and NES to calculate the internal rate of return (IRR) to undertaking a graduate job. In what follows, we first define graduates and non-graduates. On the basis of these definitions, we classify graduate jobs and non-graduate jobs, calculate the average earnings of graduate jobs and non-graduate jobs by age, and then compute the IRR.

C.1 Graduates and Non-graduates

The LFS collects individual-level data on the highest qualification that one earns, and we use this information to define graduates and non-graduates. A graduate is defined as an individual whose highest qualification is a higher-education qualification, including higher degree, National Vocational Qualification Level 5, first degree, and other (unspecified) degrees. An individual is classified as a non-graduate if her highest qualification is below a higher-education degree.

C.2 Graduate Jobs and Non-graduate Jobs

Both NES and LFS provide individual-level occupational information. However, the occupational codes and job titles vary over time, and in some cases, different occupational codes are adopted in the same year. To resolve this discrepancy, we convert each data set's occupational codes[36] to 3-digit SOC2000 (minor groups). Consistency checks are conducted on the basis of text descriptions developed by the Office for National Statistics.

Such a consistent occupational coding then allows us to work on the LFS data to classify 'graduate jobs' and 'non-graduate jobs' for each year. An occupation (at 3-digit level of SOC 2000) is defined as a graduate job if the proportion of graduates in it is no less than 50%; otherwise it is defined as a non-graduate job.

We then apply these definitions to the NES. This is done by matching SOC2000 across the LFS and NES. Since the LFS data are not available for some years before

[36]These occupational codes mainly include CODOT and the Key list of Occupations for Statistical Purposes (KOS) in earlier years, 1990 Standard Occupational Classification (SOC90), 2000 Standard Occupational Classification (SOC2000), and 2010 Standard Occupational Classification (SOC2010).

1983, the definitions derived from the 1977 LFS are used for NES 1975-1976, the 1979 LFS definitions for NES 1978, the 1981 LFS definitions for NES 1980, and the 1983 LFS definitions for NES 1982.

C.3 Construction of Internal Rate of Return

The methodology for calculating the IRR to undertaking a graduate job follows Ziderman (1973), Wilson (1980, 1983, and 1985), and Dolton and Chung (2004).

Explicitly, the IRR is found by solving for r in the following expression,

$$\sum_{t=16}^{65} \frac{B_t - C_t}{(1+r)^{t-15}} = 0 \tag{A.1}$$

where B_t, in our analysis, is interpreted as the earnings from undertaking a graduate job, and C_t is the foregone earnings that the individual could have earned in an alternative occupation, in this case, a non-graduate job.

We calculate the average earnings of graduate jobs and non-graduate jobs by age.[37] For university graduates, we assume that they enter universities at 18 and receive maintenance grants at ages 18-20. For recent cohorts who paid tuition fees and took up student loans, we also account for the fee costs and their expected lifetime loan repayments.[38] Their income profiles are therefore adjusted to include maintenance grants as well as fees and loan repayments where applicable.

Since real earnings may be expected to rise over time, it is necessary to adjust these cross-sectional age-earnings profiles to approximate the lifetime earnings patterns of given educated individuals aging over time. In practice earnings profiles are adjusted to account for the expected growth in real earnings of 2 percent per annum.[39]

Our estimates of IRR (and present values of lifetime earnings), based on the NES and LFS, date back to 1975. In order to extend the analysis of rates of return backward in time beyond 1975, we decide to refer to Wilson's related work for a proxy of IRR in the absence of superior data sets prior to 1975. Wilson (1980, 1983, and 1985) examines

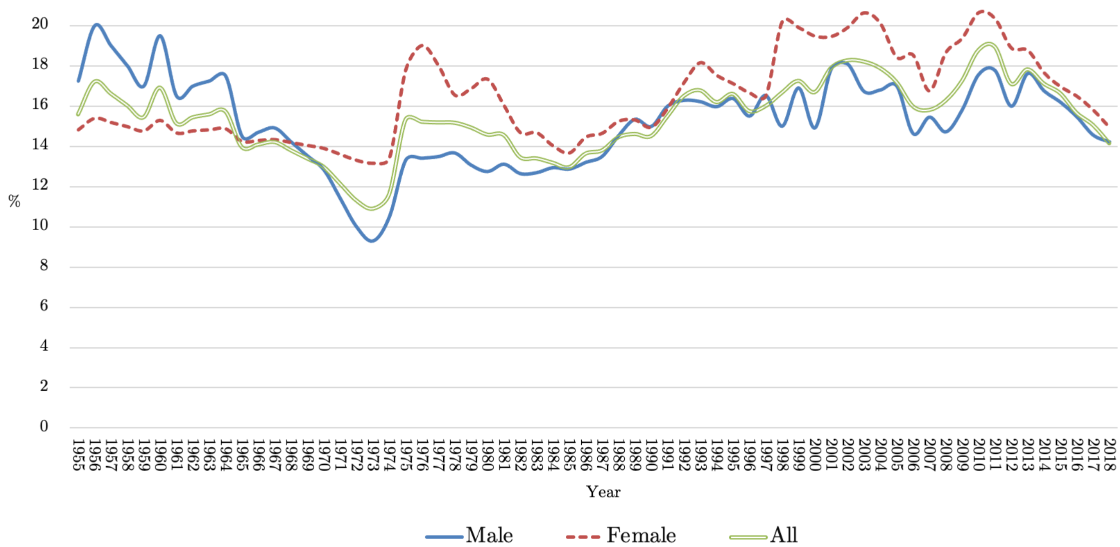
[37]We define similar samples for analysis: for NES, we use a sub-sample of full-time workers whose normal basic hours are no less than 30 per week; and for LFS, full-time employees whose total usual hours in the main job are no less than 30 hours per week.

[38]We refer to IFS's simulated data on graduates' lifetime loan repayments.

[39]This assumption is close to the sample mean of the rate of growth of per-capita Gross National Income over time for the past 65 years, which is 0.0196.

the average private rate of return for a professional scientist or engineer. In his work, B_t is the earnings of qualified scientists or engineers. The data is taken from surveys carried out by various professional institutions. The alternative income profile, C_t, represents the median earnings of all workers. The basic source for this comparison income profile is the NES, which was not started until 1968. There was no survey directly comparable to the NES prior to 1968, however. Therefore in his exercise to extend the analysis backward, Wilson claims that the comparison income profile can be regarded as stable in shape over a 10-15 year period, and adjusts the NES data according to movements in the Index of average earnings, or movements in the earnings of manual men from the DE's earnings and hours survey when the former index is unavailable. In this way, he extends the estimates back to 1955.

Figure C.1: Internal Rate of Return



Wilson does not conduct the analysis by gender, but as he argues, the proportion of females in professional institutions is very small, particularly for engineers. Therefore the estimates taken from Wilson's work are treated as IRR of males. For most of the years, Wilson provides various estimated IRR to different professional occupations. In this case, for each individual year we take averages of the estimates. In addition, for those unpublished years, the average of the estimates of the years before and after is inserted. Putting together these adjusted estimates and our results of IRR, we construct a series of males' IRR from 1955 to 2018.[40] This series of males' IRR is then utilized to run OLS regressions to predict females' IRR for the earlier years from 1955 to 1974. Figure C.1 graphs our estimates of the IRR over 1955 to 2018.

[40]It should be noted that Wilson's comparison income series is based on median incomes, while our age-earnings profiles used here are based on mean incomes. A similar exercise was actually done based on median incomes. There are not many differences between the outcomes, but the estimated IRR based on mean incomes display a more consistent pattern than Wilson's results, and therefore this is what we adopted.

Appendix D Stationarity Tests

To test whether the stochastic variables are stationary, we first perform Augmented Dickey-Fuller unit root tests. Table D1 presents the test results. The MacKinnon Approximate p values suggest that the majority of these variables are integrated of order 1, $I(1)$. As a matter of fact, most of the tests with one-lag specification overwhelmingly reject the null hypothesis of a unit root for the first differences of the variables.

A well-known weakness of the Dickey-Fuller style unit root test rests on the failure to account for structural changes. As a result, the test is biased towards the non-rejection of the unit root null in the presence of structural shifts. To overcome this complication, quite a few strategies have been devised to test for unit roots allowing for structural changes. Perron (1989) extends the Augmented Dickey-Fuller procedure by incorporating a single break in the model. In his strategy, the timing of the potential break is predetermined exogenously on the basis of an ex-post examination. This is questioned by, among others, Zivot and Andrews (1992) who develop a methodology for endogenizing the break point. Their approach allows for one structural change in the trend of the series and/or the intercept. And through a grid search, the process selects the optimal break point where the t-statistic from the Augmented Dickey-Fuller test of unit root is at a minimum, namely most negative and least favorable to the unit root null hypothesis. The test allowing for a single break point has been extended by, for example, Clemente et al. (1998) who propose unit root tests that allow for two structural changes in the mean of the series based on two models: the AO ("additive outliers") model for a sudden shift in a series and the IO ("innovational outliers") model for a gradual change.

Given the weakness of Augmented Dickey-Fuller tests, we perform the Zivot-Andrews routine to test the unit root of the first-differenced series, accounting for a single potential structural shift in the variable. As shown in Table D2, tests for most series reject the unit root null, with the exception of $\Delta \ln UEm_t$ and $\Delta \ln UEf_t$. We then use the Clemente-Montañés-Reyes unit root test with single mean shift to test the stationarity of $\ln UEm_t$, $\Delta \ln UEm_t$, $\ln UEf_t$, and $\Delta \ln UEf_t$. Test results are shown in Table D3. Despite the structural changes, we are unable to reject the null of a unit root in $\ln UEm_t$ and $\ln UEf_t$. But the null of a unit root in $\Delta \ln UEm_t$ and $\Delta \ln UEf_t$ is rejected. So we conclude that neither $\Delta \ln UEm_t$ nor $\Delta \ln UEf_t$ exhibits a unit root.

Table D1: Augmented Dikey-Fuller Unit Root Test: MacKinnon Approximate p Values

Variable	**At Level**				**At First Difference**			
	lags(1)	**lags(2)**	**lags(3)**	**lags(4)**	**lags(1)**	**lags(2)**	**lags(3)**	**lags(4)**
ln UEm_t	0.6310	0.6371	0.8014	0.8271	0.0105	0.0011	0.0006	0.0014
ln UEf_t	0.7165	0.6582	0.6607	0.6499	0.0126	0.0169	0.0061	0.0228
ln Qm_t	0.1543	0.3202	0.4438	0.6118	0.0003	0.0315	0.0744	0.0593
ln Qf_t	0.0723	0.1813	0.2867	0.4070	0.0041	0.0640	0.1965	0.1258
ln Sm_t	0.2377	0.3086	0.3660	0.4712	0.0000	0.0016	0.0032	0.0089
ln Sf_t	0.0885	0.1152	0.1906	0.2564	0.0000	0.0036	0.0154	0.0103
ln GCSEm_t	0.4372	0.4372	0.4985	0.5368	0.0000	0.0001	0.0008	0.0084
ln GCSEf_t	0.4469	0.4398	0.4924	0.5803	0.0001	0.0020	0.0107	0.0244
ln Um_t	0.3513	0.3293	0.4973	0.3360	0.0000	0.0011	0.0197	0.0231
ln Uf_t	0.3738	0.4644	0.6405	0.4064	0.0000	0.0003	0.0684	0.0735
ln GUm_t	0.0898	0.2882	0.4000	0.4015	0.0000	0.0000	0.0003	0.0016
ln GUf_t	0.0326	0.2315	0.2215	0.3714	0.0000	0.0001	0.0000	0.0005
ln YUm_t	0.4014	0.3928	0.1385	0.1461	0.0000	0.0000	0.0005	0.0146
ln YUf_t	0.5205	0.5856	0.4444	0.3315	0.0000	0.0000	0.0010	0.0359
ln IRRm_t	0.1749	0.1679	0.2716	0.2620	0.0000	0.0001	0.0030	0.0001
ln IRRf_t	0.1951	0.2718	0.3920	0.4113	0.0000	0.0000	0.0002	0.0029
ln C_t	0.1964	0.2653	0.2506	0.2282	0.0021	0.0207	0.1063	0.4194
ln LIQUIDITY_t	0.4438	0.3868	0.2508	0.2085	0.0000	0.0002	0.0042	0.0068
COST_t	0.9625	0.9540	0.9286	0.9037	0.0000	0.0007	0.0066	0.0116

Notes: To test the stationarity of the variables, we use augmented Dickey-Fuller (ADF) unit-root test where the null hypothesis of the unit root is tested against the stationarity alternative. Hamilton (1994) suggests four different cases to perform the ADF test. We decide which case to be used for each variable according to the pattern over time. Instead of reporting the ADF statistics, we tabulate the MacKinnon Approximate p values here. The p values reveal that the majority of these variables are $I(1)$. Experiments with different numbers of lag terms yield similar conclusions.

Table D2: Zivot–Andrews Unit Root Test

Variable	**At Level**						**At First Difference**					
Allowing for a break in	***Intercept (Critical values: 1%: -5.43, 5%: -4.80)***		***Trend (Critical values: 1%: -4.93, 5%: -4.42)***		***Both (Critical values: 1%: -5.57, 5%: -5.08)***		***Intercept (Critical values: 1%: -5.43, 5%: -4.80)***		***Trend (Critical values: 1%: -4.93, 5%: -4.42)***		***Both (Critical values: 1%: -5.57, 5%: -5.08)***	
	Minimum t-statistic	**Break Point**	**Minimum t-statistic**	**Break Point**	**Minimum t-statistic**	**Break Point**	**Minimum t-statistic**	**Break Point**	**Minimum t-statistic**	**Break Point**	**Minimum t-statistic**	**Break Point**
ln UEm_t	-4.530	1966	-4.055	1968	-4.747	1979	-4.351	1988	-4.023	1968	-4.704	1970
ln UEf_t	-3.727	2009	-3.414	2001	-3.633	1990	-3.970	1988	-3.489	1967	-3.948	1988
ln Qm_t	-3.789	1992	-2.578	2013	-3.729	1992	-10.611***	1988	-9.195***	1974	-10.613***	1988
ln Qf_t	-2.846	1990	-2.689	2005	-3.194	1990	-6.126***	1988	-4.409**	1975	-6.085***	1988
ln Sm_t	-3.036	1989	-2.811	1993	-3.336	1990	-7.413***	1982	-7.213***	1975	-7.662***	1982
ln Sf_t	-2.798	1963	-2.985	1992	-3.210	1990	-7.962***	1988	-7.673***	1975	-7.943***	1976
ln $GCSEm_t$	-3.606	2005	-3.110	2000	-3.861	1991	-7.214***	1988	-6.698***	1974	-7.155***	1988
ln $GCSEf_t$	-3.533	1988	-2.904	2000	-4.493	1988	-6.862***	1988	-6.085***	1991	-6.888***	1988
ln Um_t	-3.373	1997	-3.371	1984	-3.552	1980	-7.144***	1984	-6.759***	2013	-7.603***	2013
ln Uf_t	-4.122	1975	-2.734	1982	-4.128	1975	-6.107***	1985	-5.463***	2002	-6.027***	1987
ln GUm_t	-3.877	1974	-4.094	1984	-4.961	1980	-7.056***	1966	-6.819***	2009	-7.162***	1966
ln GUf_t	-3.889	1975	-3.911	1983	-4.311	1979	-6.973***	1966	-6.437***	1969	-7.235***	1966
ln YUm_t	-3.259	1967	-4.244	1982	-4.267	1980	-8.598***	1967	-8.324***	1968	-8.569***	1984
ln YUf_t	-4.355	1974	-3.498	1981	-4.799	1975	-7.821***	1985	-7.487***	1972	-8.09***	1978
ln $IRRm_t$	-4.126	1965	-4.380	1972	-5.338**	1975	-10.396***	1974	-9.350***	1989	-10.529***	1974
ln $IRRf_t$	-3.630	1991	-3.222	2010	-4.012	1998	-7.694***	2004	-7.580***	1976	-7.918***	1977
ln C_t	-2.362	2008	-4.014	2003	-3.579	2002	-7.377***	2006	-7.064***	1988	-7.344***	2006
ln $LIQUIDITY_t$	-10.697***	2006	-8.549***	2001	-10.807***	2006	-12.725***	2000	-12.264***	2012	-13.351***	2006
$COST_t$	-9.537***	1998	-5.413***	1989	-9.018***	1998	-10.691***	2001	-10.355***	1999	-10.673***	2012

*** $p < 0.01$, ** $p < 0.05$

Notes: The Zivot-Andrews test statistic reported is the minimum Augmented Dickey-Fuller statistic calculated across all potential breaks in the data for three cases:
1) a structural change in the intercept of the series is allowed for (the 1% critical value is -5.43 and the 5% critical value is -4.80);
2) a structural change in the trend of the series is allowed for (the 1% critical value is -4.93 and the 5% critical value is -4.42); and
3) a structural change in the intercept and the trend is allowed for (the 1% critical value is -5.57 and the 5% critical value is -5.08).
The break point denotes the year when this minimum ADF statistic is obtained.

Table D3: Clemente-Montañés-Reyes Unit Root Test (with Single Mean Shift) for $lnUem_t$ and $lnUEf_t$

Test for ln(UEm$_t$)

T = 53 optimal breakpoint: 1994

AR(0)	**du1**	**(rho - 1)**	**const**
Coefficient	0.778	-0.134	2.114
t-statistic	11.711	-2.537	
***p* value**	0.000	-3.560	(5% crit. value)

Test for ln(UEf$_t$)

T = 53 optimal breakpoint: 1994

AR(0)	**du1**	**(rho - 1)**	**const**
Coefficient	1.521	-0.114	1.525
t-statistic	12.391	-2.301	
***p* value**	0.000	-3.560	(5% crit. value)

Test for D.ln(UEm$_t$)

T = 52 optimal breakpoint: 1964

AR(0)	**du1**	**(rho - 1)**	**const**
Coefficient	-0.004	-0.502	0.029
t-statistic	-0.167	-3.797	
***p* value**	0.868	-3.560	(5% crit. value)

Test for D.ln(UEf$_t$)

T = 52 optimal breakpoint: 1991

AR(0)	**du1**	**(rho - 1)**	**const**
Coefficient	-0.012	-0.588	0.050
t-statistic	-0.767	-3.872	
***p* value**	0.446	-3.560	(5% crit. value)

Notes: Based on the test results we compare the absolute value of the t-statistics to the absolute values of the 5% critical value. If |t-statistics| > |critical value|, we reject the null hypothesis that a unit root with structural break is present.

Appendix E Interpretation of Coefficients

In this appendix, we explain how we can interpret the signs of the coefficients in our models as specified in equations (4) to (6). This is illustrated with an equation in the following general form:

$$\Delta \ln Y_t = \gamma + \alpha \Delta \ln X_t + \beta \Delta Z_t + \varepsilon_t. \tag{10}$$

In our models, we convert a non-stationary time series to a stationary form by differencing the natural logarithm of most of the variables (denoted by $\Delta \ln X_t$ in the equation above). The only exception is *COST* which is negative in earlier years, and we take the first difference of the original data (denoted by ΔZ_t here).

Starting with $\Delta \ln X_t$, for its coefficient we have

$$\alpha = \frac{d(\Delta \ln Y_t)}{d(\Delta \ln X_t)} = \frac{\ln\left(\frac{Y_t}{Y_{t-1}} / \frac{Y_{t-1}}{Y_{t-2}}\right)}{\ln\left(\frac{X_t}{X_{t-1}} / \frac{X_{t-1}}{X_{t-2}}\right)} .$$

This implies that

$$\frac{Y_t}{Y_{t-1}} / \frac{Y_{t-1}}{Y_{t-2}} = \left(\frac{X_t}{X_{t-1}} / \frac{X_{t-1}}{X_{t-2}}\right)^{\alpha} . \tag{11}$$

Therefore if $\alpha > 0$ and $\frac{X_t}{X_{t-1}} / \frac{X_{t-1}}{X_{t-2}} > 1$, we have $\frac{Y_t}{Y_{t-1}} / \frac{Y_{t-1}}{Y_{t-2}} > 1$.

Similarly, for ΔZ_t we can interpret its coefficient as

$$\beta = \frac{d(\Delta \ln Y_t)}{d(\Delta Z_t)} = \frac{\ln\left(\frac{Y_t}{Y_{t-1}} / \frac{Y_{t-1}}{Y_{t-2}}\right)}{\Delta Z_t - \Delta Z_{t-1}} .$$

This implies that

$$\frac{Y_t}{Y_{t-1}} / \frac{Y_{t-1}}{Y_{t-2}} = e^{\beta \cdot (\Delta Z_t - \Delta Z_{t-1})} . \tag{12}$$

If $\beta < 0$ and $\Delta Z_t - \Delta Z_{t-1} > 0$, then $\frac{Y_t}{Y_{t-1}} < \frac{Y_{t-1}}{Y_{t-2}}$.

Appendix F Additional Results

Tables 1 and 2 in Section 6 have adult unemployment (AU) included in the S equation as a proxy for labor market conditions. Here we provide additional results based on similar model specifications, except that adult unemployment is replaced by youth unemployment (YU) in the S equation. The results are shown in Tables F4 and F5.

Table F4: Structural Break Test and Estimation (1958-2018)
Model 1(b)*: Net College Cost

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Male		0.020	0.591*	0.089***	-0.745	0.010	0.085	0.759	0.249	0.023	0.163***	-0.952	-0.539***	0.028	0.363
	1975	(0.019)	(0.334)	(0.028)	(0.600)	(0.032)	(0.052)	(0.684)	(0.430)	(0.020)	(0.055)	(0.829)	(0.163)	(0.048)	(0.221)
	[1970 1980]	0.017	0.808***	0.062*	-0.362	0.016	0.052	0.064	0.228	0.002	-0.043	-0.099	-0.013	-0.050	1.170***
	1993	(0.017)	(0.264)	(0.037)	(0.402)	(0.020)	(0.049)	(0.500)	(0.153)	(0.019)	(0.044)	(0.469)	(0.206)	(0.053)	(0.251)
	[1989 1997]	0.010	-0.111	0.072	-0.100	0.002	-0.019	0.446	0.913**	0.013	-0.106	0.305	-0.068	-0.052**	0.280
		(0.010)	(0.148)	(0.068)	(0.474)	(0.013)	(0.074)	(0.604)	(0.456)	(0.011)	(0.073)	(0.543)	(0.120)	(0.025)	(0.213)
	N	61				61				61					
	R^2	0.498				0.349				0.566					
	F-Stat	4.979				2.730				4.408					
	Prob >F	0.000				0.002				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Female		0.011	0.290	0.076***	0.219	0.008	0.141***	1.130*	0.540**	0.041**	0.116**	0.511	-0.423**	-0.036	0.088
	1977	(0.017)	(0.274)	(0.024)	(0.468)	(0.020)	(0.043)	(0.576)	(0.211)	(0.016)	(0.046)	(0.534)	(0.167)	(0.036)	(0.162)
	[1974 1980]	0.023	0.488**	0.006	-0.550	0.050***	-0.062	-0.609	0.468**	0.026	-0.043	-0.095	0.197	-0.082***	0.781***
	1998	(0.016)	(0.190)	(0.044)	(0.410)	(0.019)	(0.056)	(0.505)	(0.198)	(0.021)	(0.049)	(0.458)	(0.192)	(0.025)	(0.175)
	[1995 2001]	0.009	-0.050	0.019	0.196	0.012	-0.015	-0.093	0.547	0.020*	-0.252***	0.341	-0.152	-0.026	0.296
		(0.009)	(0.167)	(0.055)	(0.509)	(0.015)	(0.102)	(0.657)	(1.010)	(0.011)	(0.091)	(0.562)	(0.141)	(0.027)	(0.308)
	N	61				61				61					
	R^2	0.455				0.560				0.720					
	F-Stat	4.219				6.509				8.585					
	Prob >F	0.000				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

*Note: Youth unemployment (YU) is used in S equation.

Table F5: Structural Break Test and Estimation (1958-2018)
Model 2(b)*: Net Liquidity

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Male		0.019	0.619*	0.085***	-0.724	0.007	0.087*	0.775	0.292	0.023	0.161***	-0.911	-0.531***	-0.096	0.352
	1975	(0.019)	(0.341)	(0.029)	(0.615)	(0.032)	(0.052)	(0.688)	(0.433)	(0.020)	(0.054)	(0.810)	(0.157)	(0.191)	(0.220)
	[1971 1979]	0.010	0.767***	0.070**	-0.308	0.026	0.030	-0.042	0.208	-0.003	-0.045	0.082	0.088	0.302***	0.859***
	1998	(0.015)	(0.249)	(0.034)	(0.396)	(0.017)	(0.045)	(0.476)	(0.147)	(0.016)	(0.042)	(0.432)	(0.197)	(0.081)	(0.213)
	[1995 2001]	0.012	-0.105	0.091	0.001	0.000	0.002	0.194	0.945	0.017	-0.113	0.146	-0.095	-0.093	0.271
		(0.010)	(0.159)	(0.085)	(0.562)	(0.015)	(0.087)	(0.788)	(0.711)	(0.012)	(0.080)	(0.606)	(0.118)	(0.079)	(0.242)
	N	61				61				61					
	R^2	0.473				0.341				0.581					
	F-Stat	4.533				2.627				4.723					
	Prob >F	0.000				0.003				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Female		0.011	0.298	0.076***	0.218	0.008	0.141***	1.130*	0.539**	0.040**	0.114**	0.493	-0.422**	0.124	0.108
	1977	(0.017)	(0.274)	(0.024)	(0.468)	(0.020)	(0.043)	(0.576)	(0.211)	(0.016)	(0.045)	(0.536)	(0.165)	(0.138)	(0.158)
	[1974 1980]	0.023	0.486**	0.005	-0.549	0.050***	-0.062	-0.609	0.468**	0.022	-0.053	-0.006	0.177	0.253***	0.682***
	1998	(0.016)	(0.190)	(0.044)	(0.410)	(0.019)	(0.056)	(0.505)	(0.198)	(0.020)	(0.049)	(0.446)	(0.189)	(0.074)	(0.178)
	[1995 2001]	0.009	-0.053	0.017	0.192	0.012	-0.015	-0.095	0.533	0.023**	-0.188**	0.428	-0.271*	-0.104	0.247
		(0.009)	(0.167)	(0.055)	(0.509)	(0.015)	(0.102)	(0.658)	(1.010)	(0.011)	(0.092)	(0.562)	(0.151)	(0.079)	(0.296)
	N	61				61				61					
	R^2	0.455				0.560				0.725					
	F-Stat	4.229				6.505				8.886					
	Prob >F	0.000				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

*Note: Youth unemployment (YU) is used in S equation.

Appendix G Robustness Checks

In this appendix, we first provide the results for a shorter time period from 1975 to 2015, as shown in Tables G6 to G9. This is to address two issues with the data. First, our data on variable IRR is subject to potential inconsistency because we refer to Wilson's earlier work (Wilson, 1980, 1983, and 1985) for the pre-1975 data. Second, as can be seen in Figure 1, there is a decline in qualified leaver rate towards the end of our sample period of time. This is because of a few changes in both statistical methods and government policies in England since 2016, including the implementation of a new "16-18 school and college accountability system" in 2016 and the introduction of reformed GCSE in 2017. As such, the official statistics since 2016 relating to 'A' level and other 16-18 examination results are not directly comparable to those of earlier years. This could lead to inconsistent data on qualified leavers for the years from 2016 to 2018.

As another robustness check, we re-estimate the main regressions but with the structural break points imposed at years 1998, 2006, 2012, which are in line with the three major reforms that took place in UK's HE finance policies over the past few decades. Table G10 reports the coefficients of net college cost or net liquidity in the UE equation, over the entire sample for the years from 1958 to 2018.

Table G6: Structural Break Test and Estimation (1975-2015)
Model 1(a)*: Net College Cost

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Male		-0.001	0.306	0.201***	0.127	-0.012	-0.004	0.620*	-0.007	-0.010	-0.107***	0.166	0.362**	-0.044	0.410
	1988	(0.016)	(0.253)	(0.059)	(0.398)	(0.014)	(0.039)	(0.335)	(0.114)	(0.014)	(0.032)	(0.364)	(0.139)	(0.032)	(0.283)
	[1987 1989]	0.003	1.142***	0.005	-0.886	0.060***	0.087*	-0.988	0.373	0.030	0.019	-0.006	0.184	-0.124***	0.741**
	2002	(0.021)	(0.365)	(0.058)	(0.637)	(0.019)	(0.050)	(0.612)	(0.233)	(0.023)	(0.070)	(0.726)	(0.261)	(0.027)	(0.293)
	[2001 2003]	0.016*	-0.094	0.012	-0.120	0.013	-0.016	-0.095	0.670	0.010	-0.145***	0.408	-0.046	-0.036**	0.511
		(0.009)	(0.142)	(0.057)	(0.542)	(0.011)	(0.051)	(0.563)	(0.498)	(0.011)	(0.049)	(0.469)	(0.084)	(0.018)	(0.336)
	N	41				41				41					
	R^2	0.554				0.632				0.781					
	F-Stat	4.221				5.871				8.286					
	Prob >F	0.000				0.000				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Female		0.028	-0.235	0.048	-0.381	-0.005	-0.013	0.515	0.146	0.039**	-0.251***	0.005	0.414***	-0.103**	0.204
	1986	(0.019)	(0.441)	(0.053)	(0.441)	(0.013)	(0.038)	(0.341)	(0.098)	(0.015)	(0.055)	(0.393)	(0.122)	(0.040)	(0.247)
	[1987 1989]	0.015	0.338*	-0.037	-0.221	0.082***	-0.009	-0.873**	0.462*	-0.005	0.071	0.570	-0.378	-0.097***	1.234***
	1998	(0.020)	(0.201)	(0.059)	(0.522)	(0.018)	(0.050)	(0.415)	(0.252)	(0.035)	(0.056)	(0.596)	(0.286)	(0.024)	(0.324)
	[1997 1999]	0.010	-0.061	0.030	0.326	0.028***	-0.049	-0.479	-0.148	0.016	-0.264***	0.289	-0.136	-0.030	0.575
		(0.009)	(0.157)	(0.064)	(0.617)	(0.010)	(0.057)	(0.412)	(0.608)	(0.014)	(0.069)	(0.465)	(0.109)	(0.021)	(0.496)
	N	41				41				41					
	R^2	0.369				0.756				0.839					
	F-Stat	1.866				10.870				12.156					
	Prob >F	0.051				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

*Note: Adult unemployment (AU) is used in S equation.

Table G7: Structural Break Test and Estimation (1975-2015)
Model 1(b)*: Net College Cost

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Male		0.006	0.432*	0.129***	-0.081	-0.013	0.003	0.643*	0.010	-0.009	-0.103***	0.158	0.344***	-0.043	0.425*
	1988	(0.016)	(0.247)	(0.042)	(0.384)	(0.014)	(0.041)	(0.350)	(0.119)	(0.012)	(0.029)	(0.322)	(0.123)	(0.028)	(0.250)
	[1987 1989]	-0.001	1.172***	0.019	-0.872	0.039**	0.038	-0.676	0.630***	0.037**	0.003	0.197	0.006	-0.114***	0.708***
	2002	(0.020)	(0.346)	(0.044)	(0.631)	(0.017)	(0.046)	(0.584)	(0.208)	(0.017)	(0.056)	(0.608)	(0.093)	(0.023)	(0.176)
	[2001 2003]	0.015	-0.120	0.051	-0.119	0.016	0.007	-0.174	0.506	0.001	-0.215***	-0.656	-0.329***	-0.030*	0.570*
		(0.010)	(0.182)	(0.102)	(0.767)	(0.013)	(0.060)	(0.733)	(0.608)	(0.010)	(0.048)	(0.524)	(0.105)	(0.017)	(0.304)
	N	41				41				41					
	R^2	0.540				0.596				0.830					
	F-Stat	3.958				5.058				11.165					
	Prob >F	0.000				0.000				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta COST_t$	ΔlnQ_t
Female		0.021	-0.166	0.071*	-0.325	-0.006	-0.003	0.548	0.140	0.038**	-0.249***	0.003	0.411***	-0.099**	0.222
	1986	(0.018)	(0.399)	(0.039)	(0.426)	(0.013)	(0.039)	(0.342)	(0.099)	(0.015)	(0.055)	(0.393)	(0.122)	(0.040)	(0.247)
	[1985 1987]	0.019	0.368*	-0.003	-0.311	0.081***	-0.008	-0.853**	0.489*	-0.005	0.072	0.573	-0.387	-0.098***	1.235***
	1998	(0.019)	(0.199)	(0.050)	(0.499)	(0.018)	(0.050)	(0.416)	(0.256)	(0.035)	(0.056)	(0.595)	(0.286)	(0.024)	(0.324)
	[1997 1999]	0.010	-0.044	0.008	0.182	0.027***	-0.052	-0.472	-0.088	0.016	-0.263***	0.286	-0.135	-0.031	0.564
		(0.009)	(0.159)	(0.054)	(0.502)	(0.010)	(0.058)	(0.413)	(0.600)	(0.014)	(0.069)	(0.465)	(0.109)	(0.021)	(0.496)
	N	41				41				41					
	R^2	0.410				0.758				0.838					
	F-Stat	2.164				10.849				12.165					
	Prob >F	0.021				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

*Note: Youth unemployment (YU) is used in S equation.

Table G8: Structural Break Test and Estimation (1975-2015)
Model 2(a)*: Net Liquidity

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Male		-0.000	0.284	0.201***	0.134	-0.014	0.006	0.650*	0.023	-0.008	-0.098***	0.123	0.312**	0.123	0.492**
	1988	(0.016)	(0.253)	(0.059)	(0.398)	(0.014)	(0.041)	(0.350)	(0.119)	(0.012)	(0.028)	(0.316)	(0.122)	(0.080)	(0.246)
	[1986 1990]	-0.003	1.187***	0.005	-0.787	0.038**	0.037	-0.671	0.630***	0.017	0.020	0.055	0.060	0.315***	0.640***
	2002	(0.021)	(0.359)	(0.056)	(0.591)	(0.017)	(0.046)	(0.584)	(0.208)	(0.018)	(0.051)	(0.569)	(0.094)	(0.060)	(0.161)
	[2001 2003]	0.017*	-0.068	0.008	-0.087	0.017	0.007	-0.221	0.450	0.004	-0.199***	-0.621	-0.358***	-0.072*	0.516*
		(0.009)	(0.174)	(0.057)	(0.765)	(0.013)	(0.060)	(0.733)	(0.608)	(0.010)	(0.048)	(0.516)	(0.102)	(0.043)	(0.302)
	N	41				41				41					
	R^2	0.553				0.595				0.835					
	F-Stat	4.171				5.039				11.512					
	Prob >F	0.000				0.000				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnAU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Female		0.026	0.155	0.021	-0.198	-0.004	-0.023	0.628*	0.135	0.034**	-0.190***	-0.191	0.252**	0.267**	0.226
	1988	(0.019)	(0.196)	(0.047)	(0.413)	(0.013)	(0.036)	(0.332)	(0.095)	(0.015)	(0.047)	(0.370)	(0.103)	(0.110)	(0.236)
	[1987 1989]	-0.003	0.664**	-0.041	-0.289	0.074***	0.019	-1.467***	0.671***	0.071**	0.159**	-1.070	0.247	0.192***	0.386
	2002	(0.024)	(0.288)	(0.058)	(0.662)	(0.017)	(0.053)	(0.537)	(0.236)	(0.035)	(0.080)	(0.951)	(0.156)	(0.068)	(0.280)
	[2001 2003]	0.011	-0.052	0.027	0.358	0.029**	-0.051	-0.507	-0.308	0.027*	-0.088	-0.667	-0.622**	-0.151**	-0.145
		(0.010)	(0.195)	(0.067)	(0.807)	(0.012)	(0.067)	(0.495)	(0.700)	(0.015)	(0.114)	(0.546)	(0.238)	(0.069)	(0.515)
	N	41				41				41					
	R^2	0.374				0.752				0.846					
	F-Stat	1.948				10.680				12.766					
	Prob >F	0.040				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

*Note: Adult unemployment (AU) is used in S equation.

Table G9: Structural Break Test and Estimation (1975-2015)
Model 2(b)*: Net Liquidity

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Male		0.006	0.443*	0.132***	-0.078	-0.013	0.004	0.646*	0.015	-0.008	-0.095***	0.117	0.302**	0.125	0.505**
	1988	(0.016)	(0.247)	(0.042)	(0.384)	(0.014)	(0.041)	(0.350)	(0.119)	(0.012)	(0.028)	(0.316)	(0.121)	(0.080)	(0.246)
	[1987 1989]	-0.001	1.166***	0.016	-0.856	0.039**	0.038	-0.676	0.629***	0.017	0.017	0.081	0.065	0.317***	0.647***
	2002	(0.020)	(0.346)	(0.044)	(0.631)	(0.017)	(0.046)	(0.584)	(0.208)	(0.018)	(0.050)	(0.569)	(0.094)	(0.060)	(0.161)
	[2001 2003]	0.015	-0.087	0.054	-0.017	0.017	0.008	-0.223	0.447	0.005	-0.199***	-0.622	-0.357***	-0.073*	0.510*
		(0.010)	(0.182)	(0.102)	(0.766)	(0.013)	(0.060)	(0.733)	(0.609)	(0.010)	(0.048)	(0.516)	(0.102)	(0.043)	(0.301)
	N	41				41				41					
	R^2	0.540				0.596				0.835					
	F-Stat	3.980				5.042				11.490					
	Prob >F	0.000				0.000				0.000					

	Break	ΔlnS_t				ΔlnQ_t				$\Delta lnUE_t$					
	[95% CI]	Intercept	$\Delta lnGCSE_t$	$\Delta lnYU_{t-1}$	ΔlnC_t	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	ΔlnS_{t-2}	Intercept	$\Delta lnGU_{t-1}$	ΔlnC_t	$\Delta lnIRR_{t-1}$	$\Delta lnLIQUIDITY_t$	ΔlnQ_t
Female		0.021	-0.142	0.070*	-0.321	-0.006	-0.003	0.548	0.142	0.040***	-0.259***	0.022	0.417***	0.296**	0.173
	1988	(0.018)	(0.399)	(0.039)	(0.426)	(0.013)	(0.039)	(0.342)	(0.099)	(0.015)	(0.056)	(0.392)	(0.122)	(0.115)	(0.248)
	[1987 1989]	0.019	0.357*	-0.005	-0.302	0.081***	-0.007	-0.856**	0.485*	-0.015	0.063	0.643	-0.295	0.271***	1.131***
	2002	(0.019)	(0.199)	(0.050)	(0.499)	(0.018)	(0.050)	(0.416)	(0.256)	(0.035)	(0.056)	(0.600)	(0.279)	(0.068)	(0.317)
	[2001 2003]	0.010	-0.059	0.009	0.165	0.027***	-0.052	-0.469	-0.071	0.026*	-0.205***	0.315	-0.290**	-0.112*	0.266
		(0.009)	(0.159)	(0.054)	(0.502)	(0.010)	(0.058)	(0.413)	(0.599)	(0.015)	(0.070)	(0.464)	(0.116)	(0.059)	(0.471)
	N	41				41				41					
	R^2	0.409				0.758				0.840					
	F-Stat	2.145				10.846				12.207					
	Prob >F	0.022				0.000				0.000					

Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

*Note: Youth unemployment (YU) is used in S equation.

Table G10: Estimations with Structural Breaks Imposed at 1998, 2006, 2012

Break Points	Model 1(a) $\Delta\ COST_t$		Model 2(a) $\Delta\ lnLIQUIDITY_t$		Model 1(b) $\Delta\ COST_t$		Model 2(b) $\Delta\ lnLIQUIDITY_t$	
	Male	Female	Male	Female	Male	Female	Male	Female
	-0.030	-0.050**	0.147*	0.205***	-0.029	-0.049**	0.144*	0.201***
	(0.024)	(0.020)	(0.077)	(0.065)	(0.024)	(0.020)	(0.077)	(0.065)
1998								
	0.007	0.194	-0.060	0.046	0.008	0.189	-0.034	0.052
	(0.213)	(0.193)	(0.190)	(0.142)	(0.213)	(0.194)	(0.191)	(0.142)
2006								
	-0.036	-0.051	1.283	-1.332	-0.039	-0.051	1.374	-1.328
	(0.084)	(0.052)	(3.009)	(1.324)	(0.084)	(0.052)	(3.021)	(1.332)
2012								
	-0.123	-0.158	0.923	1.220	-0.118	-0.152	0.881	1.169
	(0.158)	(0.160)	(1.170)	(1.218)	(0.157)	(0.160)	(1.160)	(1.214)

Reported in this table are the coefficients of Net College Cost or Net Liquidity in the UE equation (over years 1958-2018). Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Notes:
Models 1(a) and 2(a): Adult unemployment used in S equation
Models 1(b) and 2(b): Youth unemployment used in S equation

Appendix H Variable Definitions and Data Sources

Variable	Definition	Data Source
S (male/female)	16-year-old age group attending schools and colleges of further education as a percentage of 16-year-olds	Statistics of Education Schools and Pupils in England Statistics of Education in Wales Schools in Wales Statistics of Further and Higher Education in Polytechnics and Colleges Education Statistics of the UK Education and Training Statistics for the UK Statistics of Education in Wales Higher Education, Further Education and Training Statistics in Wales National Statistics: Participation in education, training and employment Statistics for Wales: Participation of 16-30 year olds in education by mode, age and year
Q (male/female)	Qualified leavers with two or more 'A' level passes as a percentage of the relevant age groups	Statistics of Education Statistics of Education, School Leavers, CES and GCE Statistics of School Examinations, GCSE and GCE Statistics of Education, Public Examinations, GCSE & GCE Statistical First Releases *ONS*: A level and other 16 to 18 results *DCSF*: GCE/Applied GCE A/AS and Equivalent Examination Results in England Statistics for Wales: Examination achievements of pupils *ONS*: Estimates of the population
UE (male/female)	Entrants to first-degree courses as a percentage of the relevant age groups	Returns from Universities and Universities Colleges Statistics of Education University Statistics Statistics of Further and Higher Education in Polytechnics and Colleges Further and Higher Education and Training Statistics in Wales UCAS data *UCAS*: Provider-level End of Cycle Acceptances

Continued on next page

Variable	Definition	Data Source
GCSE (male/female)	School leavers with five or more A*-C as a percentage of age groups	Statistics of School Leavers, CSE and GCE Statistics of Education, School Examinations, GCSE and GCE Statistics of Education: Public Examinations, GCSE/GNVQ and GCE/AGNVQ in England GCSE/GNVQ and GCE A/AS/ADVANCED GNVQ Results for Young People in England GCSE and Equivalent Results Key Stage 4 Performance
U (male/female)	Per cent adult males/females unemployment in Great Britain	British Labour Statistics: Historical Abstract 1886-1968 Department of Employment Gazette Labour Market Trends Economic & Labour Market Review *ONS*: Claimant Count and Vacancies Time Series
GU (male/female)	Per cent unemployment of UK-domiciled males/females who obtained undergraduate qualification through full-time study	First Destination of University Graduates First Destination of Students Leaving HEIs Destinations of Leavers from HE Self-calculation for years 1955-1962 *HESA*: Destinations of Leavers from HE
YU (male/female)	Per cent unemployment among males/females aged 18 and 19	The Relative Pay and Employment of Young People by William Wells Department of Employment Gazette Self calculation based on QLFS
C	Per capita consumption expenditure (2006 price, £)	*ONS*: Annual Abstract of Statistics UK National Accounts, The Blue Book time series UK population mid-year estimate Consumer price inflation time series
IRR (male/female)	Internal rate of return to undertaking a graduate job Note: See Appendix C for details.	Wilson (1980, 1983, 1985) Self-calculation based on NES and QLFS IFS's data on graduates' lifetime loan repayments

Continued on next page

Variable	**Definition**	**Data Source**
COST	Average net college cost per student (2006 price, £1,000) Note: See Section 4.2.1 for details.	Statistics of Education Statistics of Finance & Awards Statistics of Education: Finance & Awards Statistics of Education: Student Support England and Wales Statistical First Releases *Student Loans Company*: Student Support for Higher Education in England/Wales Student Loans in England/Wales Financial Year 2020-2021
LIQUIDITY	Net liquidity available to enrolled university students (2006 price, £1,000) Note: See Section 4.2.2 for details.	Statistics of Education Statistics of Finance & Awards Statistics of Education: Finance & Awards Statistics of Education: Student Support England and Wales Statistical First Releases *Student Loans Company*: Student Support for Higher Education in England/Wales Student Loans in England/Wales Financial Year 2020-2021

Undergraduate Subject Choice: The Role of Gender, Social Class, and Expected Earnings*

Abstract

This paper explores the determinants of subject choice of undergraduate students in England and Wales, with a focus on the role of gender, social class, and students' expectations of future earnings. Using Student Income and Expenditure Survey 2004/05, along with exogenous income data, we find significant gaps by gender and across social classes in subject choice. Moreover, our analysis suggests that expected earnings matter significantly, although the impact appears to vary across fields of study.

Key words: College major; Educational choice; Expected earnings
JEL: D84, I21, I23

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1 Introduction

Education is among the most important investments in human capital. Standard models of human capital investment suggest that individuals make schooling decisions by weighing returns to education against costs associated with schooling (e.g., Becker, 1964; Mincer, 1974). Investment in education is made when marginal benefits outweigh marginal costs. And its impact is profound: educational attainment boosts one's productivity, leading to a rise in the wage premium associated with a college degree. This could also imply that the monetary gains are differentiated by the field of study in college. What's more, the difference in monetary returns, along with the difference in non-pecuniary factors, could in turn explain the variance in one's choice of college major. This paper investigates the determinants of subject choice at the undergraduate level, highlighting the role of gender, social class, and individuals' field-specific expectations of future earnings.

It is important to address the issue of subject choice in that students select education not only by level but also by type. Specifically, in addition to deciding on the number of years of education (level of schooling), the selection process also involves choosing the field of study (type of schooling) given an educational level. This is especially the case in the UK, where students make education decisions in both dimensions over different educational stages. In particular, pupils study several subjects in secondary education for the General Certificate of Secondary Education (GCSE) qualifications and take exams at the end of Year 11. Subsequently, most students who do not enter training or the labor market will stay on in school for a two-year course, before taking the Advanced Level ('A' Level) examinations at the age of 18. Those who pass three or more 'A' levels are qualified to apply to university. And then comes an important decision to make: during the application, they need to declare what college major to specialize in.

From society's point of view, it is imperative that type of education, especially in the higher education (HE) system, adapt to the ongoing structural shifts in the labor force. Despite that the labor force is becoming more educated over time in terms of level of schooling,[1] there exist sector-specific labor shortages amid the changing

[1]For example, nowadays in the UK, the majority of young adults participate in HE. In England, 53.4 percent of 17 to 30-year-olds were estimated to start HE for the first time in academic year

global workforce environment. Existing evidence suggests significant shortfalls of highly skilled workers in some fields in the UK (e.g., Industrial Strategy Council, 2019; Allas et al., 2019). In particular, emerging technologies, notably automation and artificial intelligence (AI), could result in widespread skill shortages, especially in digital skills and specialist skills in "STEM" (Science, Technology, Engineering, and Mathematics). Moreover, the skill shortages are projected to worsen substantially by 2030. This has reinforced the concerns about subject-related college choices. As such, social resources need to be allocated more efficiently among institutions, and policy interventions should be targeted at type of education besides the quantity of schooling.

Better understanding of the choice of college major can help to develop more suitable programs and curricula that are adapted to the workforce dynamics. More importantly, it may shed light on how to address sector-specific labor shortages. This has called for related research investigating why prospective HE students choose a specific course to study in university. Motivated by this issue, our paper contributes to the growing literature on college students' choice of field of study. Specifically, we examine the determinants of subject choice at the undergraduate level in England and Wales, using the 2004/05 Student Income and Expenditure Survey. Our study differs from most of the previous UK studies in that we use exogenous income data to calculate the annual earnings of earlier cohorts, which are then used as a proxy for college students' expected earnings.

Our results suggest substantial gaps in students' choice of college major by gender and across social classes. In particular, both the basic descriptive statistics and multinomial logistic regressions suggest that female students tend to choose Arts and Humanities but are more likely to avoid STEM-related fields. On the other hand, compared to the lowest socio-economic status (SES) group, children of higher social class tend to opt for Arts and Humanities. In addition, expected earnings are found to be positively correlated with the probability of choosing Professional Subjects or Engineering and Applied Subjects, whereas the opposite applies to the choice of the remaining three subject groups: Science, Social Science, and Arts and Humanities.

2019/20. (Source: Higher Education Initial Participation Rate (HEIPR) published by the Department for Education.). Meanwhile, according to OECD (2022), the UK's completion rate of full-time students who entered a bachelor's (or equivalent level) program reached 69% in 2020, being the highest among comparable developed countries.

The remainder of this paper is organized as follows. Section 2 gives a brief overview of the literature that provides empirical evidence related to subject choice. Section 3 discusses the main features of the data set and the exogenous data on earnings we use in our analysis. Section 4 describes the econometric specifications, and Section 5 presents our empirical results. Section 6 concludes.

2 Related Literature

2.1 Heterogeneity in Labour Market Payoffs to Majors

A large volume of research has studied returns to the attainment level of schooling (e.g., Cameron and Heckman, 1998, 2001; Keane and Wolpin, 2001; Meghir and Rivkin, 2011). There is also parallel literature that differentiates between college majors to examine the heterogeneity in labor market payoffs. Returns to college degrees are shown to vary across fields of education, as suggested by James et al. (1989), Grogger and Eide (1995), Hamermesh and Donald (2008), Kinsler and Pavan (2015), Kirkeboen et al. (2015), and Altonji and Zimmerman (2017) among others.

Looking at the literature in the context of UK higher education, the research related to subject choice has received growing attention. Smith et al. (2000) and Bratti et al. (2004) focus on undergraduate leavers from UK universities and show that university subject field is one of the major determinants of graduate employment. Chevalier (2011) estimates field-specific wage differentials and establishes that earnings vary substantially by subject and also across gender, within subjects. Focusing on the internal rate of return, Walker and Zhu (2011) observe high returns for women which do not differ by subject, whereas for men, there are substantial variations in returns to different subjects, with significantly higher payoffs to Law, Economics, and Management. The findings are broadly consistent with a more recent study by Britton et al. (2022) who examine the variance in the economic returns - measured by earnings at age 30 - to different subject-university combinations.

2.2 Determinants of Subject Choice

Another branch of literature further explores the underlying factors that influence individuals' investment in specific fields of study.

Using panel data from the 1958 National Child Development Study (NCDS), van de Werfhorst et al. (2003) analyze subject choice in Britain. They find a strong social class impact on the tertiary level subject choice for students from professional class backgrounds, who tend to choose Medicine and Law in university.[2] The paper also observes a strong influence from ability, comparative advantage in reading, and prior attainments in certain subjects. Furthermore, gender gaps are found in subject choice, with women underrepresented in subjects such as Medicine and Law, Engineering, Science, and Economics.

Focusing on social class influences, Bratti (2006) investigates degree subject choice at the undergraduate level in the UK, and finds no heterogeneity across socio-economic classes in the probability of enrolling in the different subject groups. As the study draws on information from Universities' Statistical Record for the period 1981-1991, which predates the introduction of student loans and tuition fees, the author suggests that the more generous student funding arrangement could have attenuated the gap in socio-economic classes as far as degree subject is concerned.

With an emphasis on socio-economic and gender gaps, Campbell et al. (2022) analyze the matches between student and degree quality. In their study, student quality is represented by students' exam scores at the age of 18, while degree quality is measured by the achievement in degrees and graduate earnings of an earlier cohort of university graduates. Using schools and universities data linked with tax records, they demonstrate substantial socio-economic inequalities in both measures of match, with disadvantaged students more inclined to attend degrees that yield lower labor market payoffs. Significant gender gaps are also found in earnings-based match: female students tend to study degrees that are equally academically selective as male students but that are associated with lower earning outcomes.

Turning now to the literature beyond the context of the UK, Montmarquette et al. (2002) explicitly examine the effect of expected labor market payoffs. In their analysis, labor market outcomes are measured by students' perceived probability of success in education, predicted graduate earnings by major, and alternative earnings in the case of dropout from college. The study highlights that the expected earnings variable plays

[2]However, as the authors acknowledge, this result might be due to the nature of the data which is characterized by a very particular and selected group with only a small proportion of the working class entering HE.

a key role in the choice of college majors. Moreover, this effect varies across gender and races: the influence is found to be larger for men as opposed to women, and for non-white students versus white students.

The effect of expected earnings on college major choice has also been investigated by Boudarbat and Montmarquette (2009) who use exogenous income data to adjust for selectivity bias. Instead of using data on students' own earnings which are only observable after they have completed schooling, the authors refer to the income data from preceding cohorts, which is available to students at the time of choosing fields of study. Initial annual earnings and the growth rate of earnings are estimated based on the exogenous information from earlier cohorts. These two measures of earnings are then used to approximate the expected earnings of students in a given cohort. By doing so, the authors reveal that, for students whose parents do not hold a university degree, the expected earnings have a significant and positive impact on the choice of field of study.

Beffy et al. (2012) also investigate the determinants of college subject choice by controlling for dynamic selection in a framework characterized by a three-stage schooling decision model. The authors examine exogenous variation in the relative returns to college majors across the French business cycle, with an emphasis on the influence of expected earnings. Their analysis indicates significant but quantitatively small elasticity of subject choice with respect to expectations of future earnings. In light of this finding, they conclude that non-pecuniary factors are important in explaining variations in subject choice.

An abundance of research has examined college subject choice with an emphasis on subjective expectations (e.g., Zafar, 2011; Arcidiacono et al., 2012; Kaufmann, 2012; Stinebrickner and Stinebrickner, 2012; Patnaik et al., 2022). Using data on subjective expectations about field-specific outcomes, Zafar (2013) analyzes the gender difference in the choice of college major. He highlights that non-pecuniary factors, such as enjoying coursework and gaining the approval of parents, dominantly determine students' college major choices, with a larger influence for females compared with males. In contrast, the gender difference in the expectations about earnings is insignificant in explaining the gender gap in college major choices. Stinebrickner and Stinebrickner (2014) compare undergraduates' initial beliefs about outcomes in college majors (upon university entrance) with the actual outcomes of final majors (at the time of leaving college). They find that future grade performance plays a key role in the decision on choice of field of study, while the effect of future earnings is statistically significant but smaller in magnitude. Based on a structural model of college major choice, Wiswall and Zafar (2015) exploit an information experiment to investigate the determinants of subject choice. In line with Zafar (2013)'s findings, their study suggests that, although expected earnings and perceived abilities are both significant in explaining college major choice, unobserved "tastes" - such as enjoyability of coursework - exert a dominant influence on the choice of major.

3 Data and Variables

3.1 Data

This paper employs individual-level data from the 2004/05 Student Income and Expenditure Survey (SIES 2004/05). The SIES 2004/05 is a large-scale survey conducted from January to April in 2005, amongst a random sample of about 3,700 full-time and part-time undergraduate students. The sample consists of England- or Wales-domiciled students studying at a higher education institution, further education institution, or Open University in England and Wales. The data set contains rich information on personal characteristics, family background,[3] students' income, expenditure, debt, savings, etc.[4]

Table 1 compares basic descriptive statistics of this survey versus the student statistics of the same year from the Higher Education Statistics Agency (HESA). As shown in the table, male students make up a smaller proportion of both the SIES respondents and the university going population in HESA's data. Besides, in the SIES sample,

[3]With respect to students' socio-economic status, the survey provides separate information for three different sub-groups, based on full-time independent students' last paid job prior to their course of study, part-time students' current or last paid job, and for full-time dependent students the occupation of the family's main income earner. On account of this difference, we include dummy variables for full-time and dependent students in our main regression on the full sample in Section 5. In Appendix D, we present a different setting without these dummy variables, while with the sample restricted to full-time dependent students only.

[4]Despite that the survey provides extensive information related to students' cost of living, in-school working hours, debt, and parental contributions, this paper concentrates on the factors that could be associated with the students' decisions on college majors, as detailed later in this section.

Table 1: SIES 2004/05 and HESA 2004/05

	SIES 2004/05	HESA 2004/05
Male	32.36%	40.97%
Proportion of First-year Full-time Students Aged 24 and Under	77.11%	84.75%
Among Male Students	82.81%	89.01%
Among Female Students	74.66%	81.41%
Proportion of First-year Part-time Students Aged 24 and Under	18.90%	18.09%
Among Male Students	28.87%	21.06%
Among Female Students	13.92%	16.58%
Proportion of Full-time Students	72.65%	63.31%
Among Male Students	72.54%	68.05%
Among Female Students	72.69%	60.01%

Note: The HESA 2004/05 data in this table refers to UK-domiciled full-time and part-time undergraduates in England and Wales institutions.

Sources: SIES 2004/05; HESA: Students in Higher Education 2004/05

the proportion of young students (aged 24 and under) among first-year full-time students is lower compared with the HESA data. Whereas the fractions of young students among first-year part-time students are very close in the two data sets. In addition, it is indicated that full-time students are relatively more represented in the SIES.

One limitation of the SIES data is that it does not provide information related to students' prior academic achievement or their beliefs about academic performance which could be important determinants of undergraduate subject choices (see, e.g., Altonji et al., 2016; Owen, 2022; Dahl et al., 2023). In addition, the data set lacks information about students' expected earnings before they chose their field of study, which we will further discuss in Section 3.3.1.

Also worth mentioning is that the SIES 2004/05 represents a different HE finance regime than that of nowadays, as it predates several substantial HE funding reforms which took effect after the survey. Specifically, the cohort of students in the survey was charged upfront tuition fees; starting from 2006/07, new student support arrangements were implemented in England and Wales higher education institutions, with variable fees charged to new university entrants and repayable after graduation through government-subsidized fee loans. However, as Finch et al. (2006) point out, the purpose of the survey was to set a baseline against the proposed changes following the 2004 Higher Education Act.

Moreover, despite being a bit outdated in terms of policy setting, the data set provides a general picture of the UK HE system and conveys the characteristics of HE students. Importantly, based on the data, both the basic descriptive statistics and regressions indicate significant gaps in students' subject choice by gender. As a matter of fact, these gender differences persist over time since the data was collected, despite the soaring costs of HE. In particular, female students remain underrepresented in STEM-related fields nowadays, even though they still account for more than half of the university going population.[5] According to HESA's HE student statistics, among the college students who enrolled in STEM-related subjects in England and Wales institutions, the proportion of female students was 37.98% in the 2004/05 academic year and 31.43% in 2020/21. In addition, the fraction of female students in Engineering and Applied Subjects was just 22.13% in 2004/05 and further dropped to 20.39% in 2020/21.[6] As such, the SIES 2004/05 provides a relevant setup to examine college students' subject choice from a policy perspective. And our analysis based on the data set nonetheless affords an insight into college major decisions, especially in explaining the gender gap in the choice of STEM degree fields.

3.2 Dependent Variable

The outcome variable considered in our analysis is undergraduate students' choice of field of study. Considering the sample size, we categorize the college majors into the following five broad groups to characterize subject choices: (i) Science, (ii) Social Science, (iii) Arts and Humanities, (iv) Engineering and Applied Subjects, and (v) Professional Subjects (including medicine and dentistry, subjects allied to medicine, veterinary science, and law).[7]

Not all of these definitions concur with the subject groupings adopted in a strand of

[5] As of the academic year of 2020/21, 56.52% of undergraduates in England and Wales institutions are female students. (Source: Higher Education Student Statistics 2020/21.)

[6] Author's calculations based on HESA's data on HE student numbers. (Sources: Students in Higher Education 2004/05 and Higher Education Student Statistics 2020/21.)

[7] Appendix A provides more details of these subjects.

UK literature, however. For instance, Walker and Zhu (2011) and Britton et al. (2022) group degree subjects to broad degree fields including STEM (Science, Technology, Engineering, and Mathematics), LEM (Law, Economics, and Business/Management), and other subject areas such as "other social sciences" as well as Arts and Humanities. Whereas we divide STEM-related subjects into two groups, Science and Engineering & Applied Subjects, by reason of the different attributes of these two degree fields. Specifically, there is an evident gender gap in Engineering (and Applied Subjects) which is much larger than that in Science. According to HESA's aggregate data on HE student numbers, in 2004/05 academic year, female students accounted for more than half (54.64%) of the students majoring in science, whereas only 22.13% of engineering students were women.[8] Therefore, it would be interesting to examine the two subject groups separately using the individual-level data from SIES.

In addition, our analysis does not choose the subject grouping of LEM, mainly constrained by the definition and classification of subject fields in the SIES data. In particular, the data categorizes Economics as a Social Studies subject, despite that economics majors are generally associated with higher payoffs in labor markets than other social sciences.[9] Similarly, absent detailed classification of business/management majors, the data set only provides information about a broad subject that is related to management: Business and Administrative Studies, which we therefore include in the Social Science group.

Another subject category to be noted is Professional Subjects which is composed of different related majors, including Medicine and Dentistry, Subjects Allied to Medicine, Veterinary Science, and Law. Among these fields, Subjects Allied to Medicine might be an outlier, usually with a larger female share and lower earning potentials. However, due to the lack of detailed classifications within this subject, we have to categorize it as a professional subject. We must acknowledge that this is a limitation of our subject grouping, which we will address in the following analysis.[10]

[8] Source: HESA Students in Higher Education 2004/05.

[9] As Bleemer and Mehta (2022) suggest, about half of the wage returns in higher-paying occupations can be attributed to economics education and majors.

[10] We will closely examine the decomposition of Professional Subjects in Section 3.3 when we discuss the characteristics of subject choices based on Figure 1c, and in Section 5 when we interpret the empirical results.

3.3 Control variables

Based on the survey, the institution type is categorized into four broad groups: pre-1992 HEIs, post-1992 HEIs, FEIs, and open universities.[11] In this paper we define the institution type based on this information, except that Oxford and Cambridge universities are grouped together as a separate type of institution: Oxbridge. Thus we have five types of institution types in the data: Oxbridge, pre-1992 HEIs, post-1992 HEIs, FEIs, and open universities. As our main interest is students in higher and further education institutions, in the following analysis we focus on the first four types of institutions.[12]

Family socio-economic status (SES) can play a crucial role in determining an individual's subject choice. Therefore, for explanatory variables we first account for social classes which are classified into six groups:

I - Managers and Administrators;

II - Professional Occupations;

III - Associate Professional and Technical Occupations;

IV - Clerical Occupations;

V - Manufacturing crafts, Personal and Protective Services;

VI - Sales Occupations; Plant and Machine Operatives; Others.

In addition, we control for other personal characteristics including gender, age, ethnicity, marital status, type of school attended (state or independent/private), and parents' educational background (measured by whether parents studied in HE).[13]

Detailed definitions of the key variables can be found in Appendix A. Table 2 provides sample descriptive statistics. In addition, Figure 1 displays the variations in the percentages of each subject choice for each category of social class, institution type, gender, and parents' HE, respectively. Table 3 summarizes the difference in the proportions of a specific subject across social classes, institution types, gender, and parents'

[11]Post-1992 HEIs are former polytechnic or central institutions that were granted university status and degree awarding power under the Further and Higher Education Act 1992; while pre-1992 HEIs are institutions that had university status before the Act came into force.

[12]The sample of the survey includes 118 individuals attending or registered at open universities. By dropping these observations and the observations missing information on college majors, we obtain a data set with a total of 3,461 observations.

[13]As discussed earlier in this section, we do not control for students' academic ability due to the lack of data on prior academic achievement.

educational attainment.

As can be seen in Figure 1a, among all the social class groups, Social Class V has the smallest proportion of students choosing Social Science as their field of study. A relatively higher proportion of students from Social Class IV attend university to study Arts and Humanities subject. Social Class III has the greatest proportion of students choosing Professional subjects as their college major.

On the other hand, Figure 1b indicates the highest proportion of students studying Professional courses and the lowest proportion studying Arts and Humanities in Pre-1992 institutions. In Oxbridge there seems to be a smaller proportion of students studying Engineering and Applied subjects, compared with other institution types. FEIs appear to have the highest proportion of students majoring in Arts and Humanities as well as Engineering and Applied subjects, and have the smallest proportion of students studying Science and Professional Subjects.

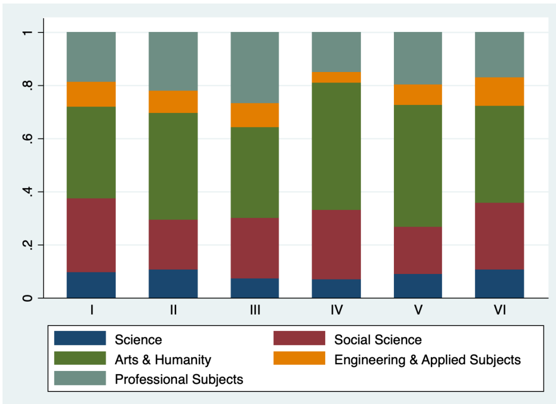
Figure 1c shows a higher male share in Social Science and Engineering and a higher female share in Arts and Humanities. At first glance, female students seem to also prefer Professional Subjects. But this could be due to the way we define this subject group. Several subjects are grouped into the broad Professional Subjects, including Medicine and Dentistry, Subjects Allied to Medicine, Veterinary Science, and Law. Indeed, as we take a closer look at the data and examine the decomposition of Professional Subjects, we can see that fewer female students major in Medicine and Dentistry as well as Law. This is shown in the lower panel of Table 3. Importantly, a larger fraction of women than men study Subjects Allied to Medicine, which is consistent with the widely known fact that women usually opt for courses in health-related topics.

Finally, compared with students whose parents do not hold an HE degree, it seems that a higher proportion of students whose parents hold an HE degree choose to study Science and Professional Subjects, while a smaller fraction of this group of students major in Arts and Humanities. The p values in Table 3 broadly confirm these patterns.

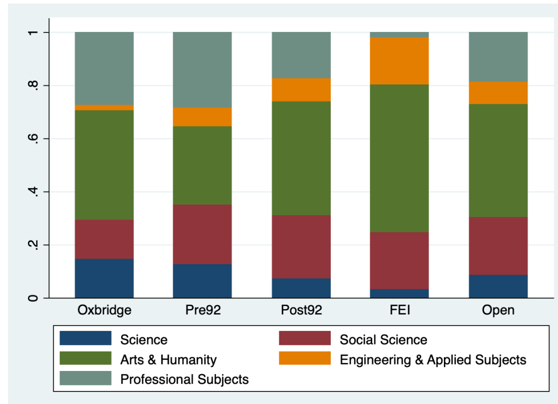
Table 2: Descriptive Statistics by Subject Group

	Science	Social Science	Arts and Humanities	Engineering and Applied Subjects	Professional Subjects	Total
Male	39.20%	34.60%	25.09%	73.44%	23.66%	32.36%
	(0.49)	(0.48)	(0.43)	(0.44)	(0.43)	(0.47)
Age	23.54	26.20	28.45	26.83	27.35	27.12
	(9.05)	(9.65)	(11.92)	(9.32)	(9.14)	(10.52)
Parents Studied in HE	54.32%	46.68%	45.58%	48.51%	52.20%	48.22%
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Social Class I	16.98%	19.49%	14.07%	18.03%	14.72%	16.04%
	(0.38)	(0.40)	(0.35)	(0.39)	(0.35)	(0.37)
Social Class II	21.60%	15.44%	18.91%	18.36%	20.08%	18.55%
	(0.41)	(0.36)	(0.39)	(0.39)	(0.40)	(0.39)
Social Class III	15.12%	19.00%	16.63%	20.00%	25.17%	19.06%
	(0.36)	(0.39)	(0.37)	(0.40)	(0.43)	(0.39)
Social Class IV	8.64%	13.11%	13.86%	5.25%	8.39%	11.37%
	(0.28)	(0.34)	(0.35)	(0.22)	(0.28)	(0.32)
Social Class V	16.67%	13.48%	20.04%	16.07%	16.64%	17.21%
	(0.37)	(0.34)	(0.40)	(0.37)	(0.37)	(0.38)
Social Class VI	20.99%	19.49%	16.49%	22.30%	14.99%	17.77%
	(0.41)	(0.40)	(0.37)	(0.42)	(0.36)	(0.38)
Married	12.04%	20.59%	26.87%	26.23%	26.69%	24.00%
	(0.33)	(0.40)	(0.44)	(0.44)	(0.44)	(0.43)
Full-time Student	87.35%	71.81%	70.65%	60.33%	76.07%	72.65%
	(0.33)	(0.45)	(0.46)	(0.49)	(0.43)	(0.45)
Dependent Student	72.22%	56.25%	54.58%	48.20%	48.42%	54.76%
	(0.45)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
School: State	87.65%	88.60%	90.26%	89.51%	83.36%	88.18%
	(0.33)	(0.32)	(0.30)	(0.31)	(0.37)	(0.32)
Institution Type: Oxbridge	4.63%	1.84%	2.99%	0.66%	3.85%	2.85%
	(0.21)	(0.13)	(0.17)	(0.08)	(0.19)	(0.17)
Institution Type: Pre92	44.75%	31.25%	24.09%	26.89%	44.57%	31.99%
	(0.50)	(0.46)	(0.43)	(0.44)	(0.50)	(0.47)
Institution Type: Post92	45.37%	58.33%	61.27%	57.05%	48.01%	56.11%
	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)
Institution Type: FEI	2.16%	5.39%	8.10%	12.13%	0.55%	5.76%
	(0.15)	(0.23)	(0.27)	(0.33)	(0.07)	(0.23)
Ethnicity: White	86.73%	82.56%	90.46%	83.61%	82.94%	86.21%
	(0.34)	(0.38)	(0.29)	(0.37)	(0.38)	(0.34)
Ethnicity: Black	3.70%	5.16%	2.70%	4.26%	5.23%	4.00%
	(0.19)	(0.22)	(0.16)	(0.20)	(0.22)	(0.20)
Ethnicity: Asian	4.94%	7.00%	2.85%	6.56%	6.60%	5.06%
	(0.22)	(0.26)	(0.17)	(0.25)	(0.25)	(0.22)
Ethnicity: Other	4.63%	5.28%	3.99%	5.57%	5.23%	4.73%
	(0.21)	(0.22)	(0.20)	(0.23)	(0.22)	(0.21)

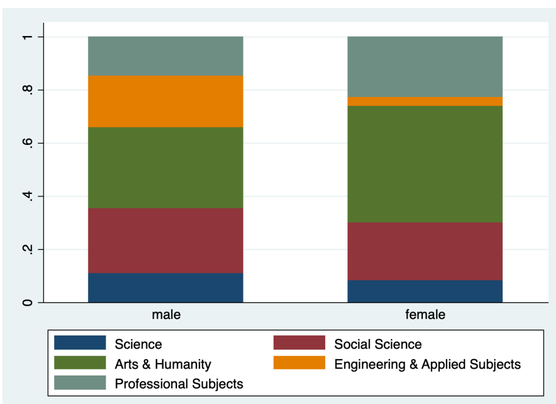
Notes: Mean in the first row. Standard deviation in the second row in parentheses.



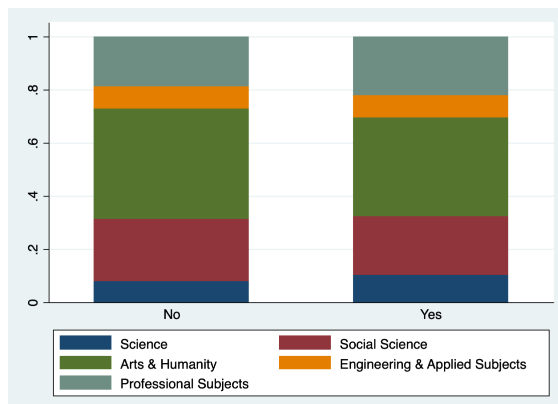
(a) Subject Choices by Social Class



(b) Subject Choices by Institution Type



(c) Subject Choices by Gender



(d) Subject Choices by Parents' HE

Figure 1: Characteristics of Subject Choices

Notes: Social class groups in Figure 1a are:
I. Managers and Administrators;
II. Professional Occupations;
III. Associate Professional and Technical Occupations;
IV. Clerical Occupations;
V. Manufacturing crafts, Personal and Protective Services; and
VI. Sales Occupations; Plant and Machine Operatives; Others.

Table 3: Characteristics of Subject Choices by Social Class, Institution Type, Gender, or Parents' HE

		Science	Social Science	Arts and Humanities	Engineering and Applied Subjects	Professional Subjects
		Difference (%) (p value)	Difference (%) (p value)	Difference (%) (p value)	Difference (%) (p value)	Difference (%) (p value)
Social Class	II - I	0.960 (0.576)	**-8.724 (0.000)**	**5.565 (0.044)**	-1.148 (0.481)	3.347 (0.145)
	III - I	-2.397 (0.125)	**-4.973 (0.043)**	-0.184 (0.946)	-0.638 (0.697)	**8.192 (0.001)**
	IV - I	-2.702 (0.134)	-1.410 (0.624)	**13.417 (0.000)**	**-5.651 (0.001)**	-3.653 (0.135)
	V - I	-0.816 (0.626)	**-9.843 (0.000)**	**11.284 (0.000)**	-1.627 (0.321)	1.002 (0.661)
	VI - I	1.110 (0.524)	-2.700 (0.287)	1.983 (0.472)	1.110 (0.524)	-1.503 (0.496)
	III - II	**-3.357 (0.030)**	**3.751 (0.091)**	**-5.749 (0.029)**	0.511 (0.740)	**4.845 (0.039)**
	IV - II	**-3.663 (0.044)**	**7.314 (0.005)**	**7.851 (0.012)**	**-4.503 (0.004)**	**-7.000 (0.005)**
	V - II	-1.776 (0.283)	-1.119 (0.606)	**5.719 (0.039)**	-0.479 (0.755)	-2.345 (0.302)
	VI - II	0.150 (0.930)	**6.024 (0.009)**	-3.582 (0.184)	2.258 (0.166)	**-4.850 (0.028)**
	IV - III	-0.305 (0.849)	3.563 (0.183)	**13.601 (0.000)**	**-5.013 (0.002)**	**-11.845 (0.000)**
	V - III	1.581 (0.293)	**-4.870 (0.030)**	**11.468 (0.000)**	-0.990 (0.523)	**-7.190 (0.002)**
	VI - III	**3.507 (0.025)**	2.273 (0.333)	2.167 (0.411)	1.748 (0.286)	**-9.694 (0.000)**
	V - IV	1.887 (0.277)	**-8.433 (0.001)**	-2.132 (0.503)	**4.023 (0.010)**	**4.655 (0.057)**
	VI - IV	**3.812 (0.038)**	-1.290 (0.641)	**-11.434 (0.000)**	**6.761 (0.000)**	2.151 (0.359)
	VI - V	1.926 (0.251)	**7.143 (0.002)**	**-9.301 (0.001)**	**2.737 (0.096)**	-2.504 (0.253)
Institution Type	(2) - (1)	-2.042 (0.555)	**7.565 (0.076)**	**-11.569 (0.015)**	**5.201 (0.045)**	0.846 (0.856)
	(3) - (1)	**-7.385 (0.006)**	**8.999 (0.036)**	1.752 (0.727)	**6.705 (0.017)**	**-10.071 (0.010)**
	(4) - (1)	**-11.308 (0.000)**	6.653 (0.163)	**14.163 (0.019)**	**16.000 (0.000)**	**-25.509 (0.000)**
	(5) - (1)	-6.231 (0.146)	7.328 (0.164)	1.196 (0.858)	**6.514 (0.034)**	-8.807 (0.120)
	(3) - (2)	**-5.343 (0.000)**	1.434 (0.359)	**13.321 (0.000)**	1.504 (0.137)	**-10.916 (0.000)**
	(4) - (2)	**-9.266 (0.000)**	-0.912 (0.772)	**25.733 (0.000)**	**10.800 (0.000)**	**-26.355 (0.000)**
	(5)- (2)	-4.189 (0.187)	-0.237 (0.953)	**12.766 (0.004)**	1.313 (0.601)	**-9.653 (0.025)**
	(4) - (3)	**-3.923 (0.035)**	-2.346 (0.449)	**12.412 (0.001)**	**9.296 (0.000)**	**-15.439 (0.000)**
	(5) - (3)	1.154 (0.641)	-1.671 (0.678)	-0.555 (0.906)	-0.191 (0.943)	1.264 (0.725)
	(5) - (4)	**5.077 (0.049)**	0.675 (0.887)	**-12.967 (0.025)**	**-9.487 (0.020)**	**16.702 (0.000)**
Gender	Male - Female	**2.827 (0.006)**	2.328 (0.120)	**-13.070 (0.000)**	**15.997 (0.000)**	**-8.081 (0.000)**
Parents have HE	Yes - No	**2.218 (0.021)**	-1.405 (0.318)	**-4.158 (0.011)**	0.100 (0.915)	**3.245 (0.016)**
		Medicine and Dentistry	Subjects Allied to Medicine	Veterinary Science	Law	
		Difference (%) (p value)	Difference (%) (p value)	Difference (%) (p value)	Difference (%) (p value)	
Gender	Male - Female	**0.103 (0.014)**	**-0.175 (0.0001)**	-0.003 (0.784)	**0.075 (0.0359)**	

Notes: Social class groups are: I. Managers and Administrators; II. Professional Occupations; III. Associate Professional and Technical Occupations; IV. Clerical Occupations; V. Manufacturing crafts, Personal and Protective Services; and VI. Sales Occupations; Plant and Machine Operatives; Others. Institution types include (1) Oxbridge, (2) pre-1992 HEIs, (3) post-1992 HEIs, (4) FEIs, and (5) open universities.

The table shows the difference in the proportions of a specific subject across social classes, institution types, gender, and parents' educational attainment. p value is the statistical significance of the difference. For instance, the proportion of individuals from social class I studying Social Science is 8.72% higher than the proportion of those from social class II studying the same subject; the p value in the parentheses indicates that the difference is significant at the 95% significance level ($0.000 < 0.05$).

3.3.1 Measuring Expected Earnings

In the standard framework of human capital investment, one of the factors driving undergraduate subject choice is students' expected labor market payoffs. The only related information in the survey is about undergraduate students' expected salaries on graduation and five years after graduation. Precautions are to be taken if we use such data on subjected expectations, however. Interviewing students who have made decisions on college majors will inevitably cause the issue of cognitive dissonance (Festinger, 1957). Consequently, data collected this way could be endogenous in that it is conditional on the major that the individual has chosen. To tackle this problem, Zafar (2013) focuses on college freshmen who have not chosen a field of study. While another study by Wiswall and Zafar (2015) creates panel data on subject choices to adjust selectivity bias. Specifically, the authors exploit an information experiment to elicit college students' initial self-belief about their expected earnings and their updated perceptions after being provided with new information on labor market prospects.

In our analysis, a major obstacle that arises with the data is that such information is not available. The survey does not provide information on students' expected wages before they decide on college majors. Nor do we observe the variation in an individual's perceptions over time regarding future labor market outcomes. An alternative measure is graduates' own earnings data. Still, this could be problematic given that the data are observed only after individuals have completed schooling, resulting in a selection problem. A typical solution to this issue is based upon a three-step methodology proposed by Heckman (1979) and Lee (1983). The procedure first estimates earnings corrected for self-selection bias, and then uses the parameters from the regression to predict future earnings for each college major (e.g., Berger, 1988; Rochat and Demeulemeester, 2001). This strategy relies crucially on instruments that satisfy exclusion restrictions, which affect subject choice without influencing individual earnings. However, we do not have such variables in the survey to perform the three-step procedure.

Another way is to use exogenous data on previous cohorts' labor market outcomes to proxy the expected earnings for a given cohort, under the assumption that students from the current cohort evaluate their earnings potential on the basis of observed graduate income. For instance, Boudarbat and Montmarquette (2009) use the lifetime earnings data of the preceding cohorts who graduated in the academic year when the cohorts of interest entered university. In a related study, Campbell et al. (2022) opt for the median earnings at the age of 26 (namely five years after graduation) of an earlier cohort. In light of these studies, the exogenous income of preceding cohorts is the form of the data we are going to use in the following analysis.

In particular, we calculate earlier cohorts' annual earnings using the cross-sectional UK Labour Force Survey (LFS) data from 1993 to 2003, combined with HESA's annual publication on First Destinations of Students Leaving Higher Education Institutions. More specifically, we base our calculation on the annual earnings of previous cohorts of graduates aged 21 to 25, by subject and by gender. Included in our regression is the natural logarithm of the median annual earnings (in 2006 price.) Appendix B describes in detail how we calculate the earnings data. A simple plot of the calculated annual earnings in Figure 2 illustrates that the payoffs to Professional Subjects are the highest among the five subject groups, while Arts and Humanities is the least lucrative field. The pattern is broadly consistent with existing evidence in the UK context (Chevalier, 2011; Walker and Zhu, 2011; Britton et al., 2016; Walker and Zhu, 2018). Compared to Arts and Humanities, other fields are found to yield higher monetary returns, usually with the highest payoffs to Medical Subjects, Business, Law, and Engineering.

Remark. Here, we assume that prospective HE students are informed about field-specific earnings by gender, so that they are able to base their expectations of future income on the population earnings. There are some rationales for making such an assumption. In reality, salary information is generally available to these students. Information about wage potentials of different courses, extracted from aggregate statistics and academic research, is easily accessible and regularly updated on social media.[14] Further, students also have the access to the information about gender pay gap by occupations, which they may directly learn from their parents and peers, observe straightforwardly from the local labor market (where men overall earn more than women), and obtain from public sources of data.[15] Moreover, considering the important role that college majors play in labor market payoffs, we might expect that potential college students have a strong incentive to acquire information on salary distributions across majors and gender.

[14]For example, *The Economist* and *The Telegraph* publish related information about field-specific median earnings, which is easily and freely accessible online to readers.

[15]In fact, gender pay gap has been widely discussed, and related information and guidance are available on a number of organizations' websites. For instance, *TUC Unionlearn*, *Careersmart*, and *Save the Student!*.

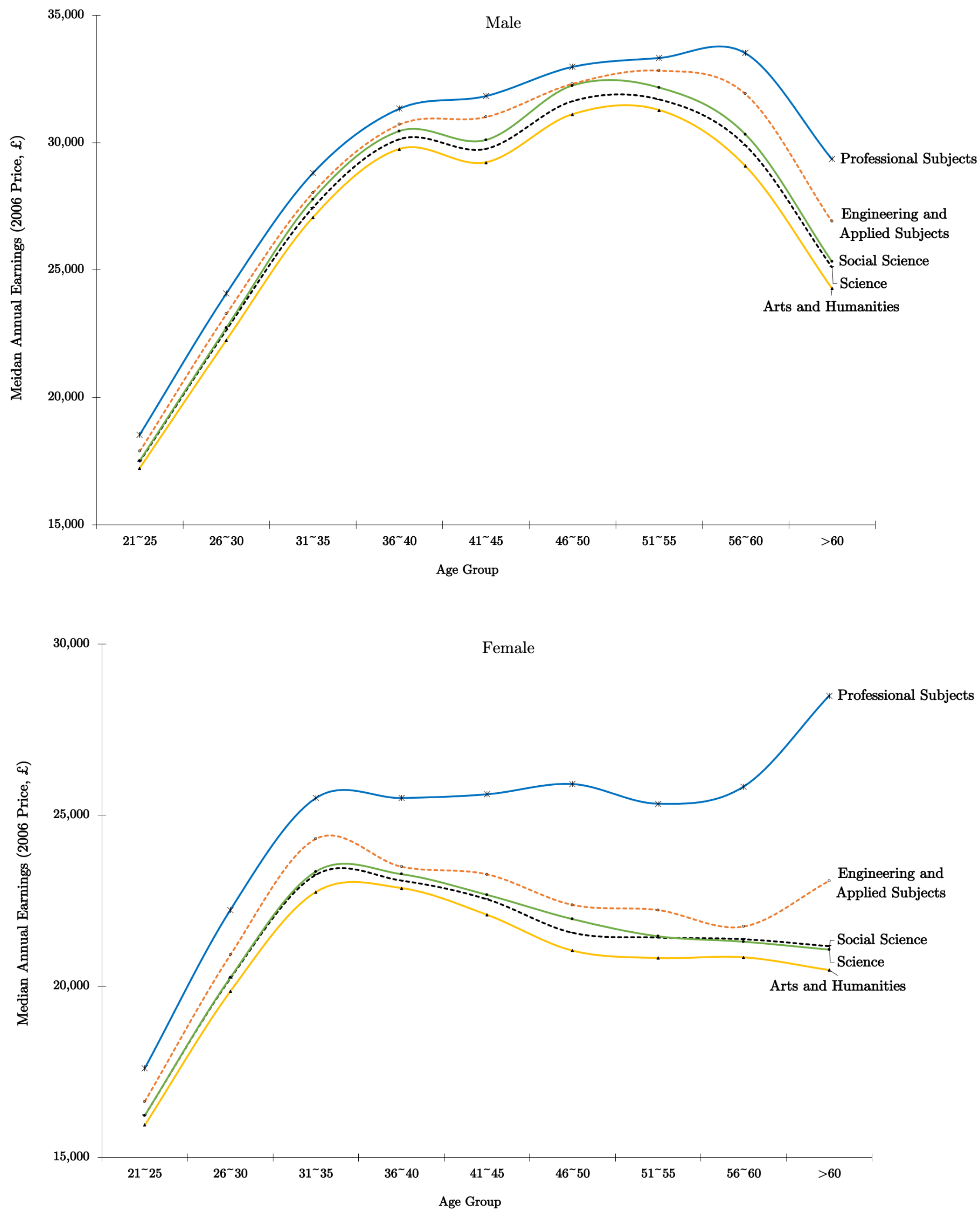


Figure 2: Annual Earnings by Faculty Groups (£)

Sources: Labour Force Survey (LFS) and First Destinations of Students Leaving Higher Education Institutions

4 Econometric Specifications

Our empirical analysis controls for a bunch of observed individual characteristics as discussed in Section 3. We assume that there are five alternatives of fields of study and that the expected utility of individual i choosing subject j is

$$U_{ji} = \alpha_j' X_i + \beta_j y_j + \epsilon_{ji}, \;\; j \in \{1, 2, 3, 4, 5\}, \tag{1}$$

where X_i is the vector of individual-specific characteristics affecting subject choices, y_j is the expected lifetime earnings in field j, and ϵ_{ji} is an unobserved component in the utility.

Our main interest is students' social class background which is included in X_i. Other control variables include individual attributes such as gender, age, ethnicity, marital status, type of school attended (state or independent/private), and type of institution attended. An additional variable related to students' family background is their parents' level of education, represented by a dummy variable indicating whether the student's parents have ever studied in HE.

As previously mentioned, the variable regarding students' socio-economic status refers to separate information on three different sub-groups, based on full-time independent students' last paid job prior to their course of study, part-time students' current or last paid job, and for full-time dependent students the occupation of the family's main income earner. On account of this difference, for our base specifications to be discussed in Section 5, we incorporate two dummy variables in the regressions on the full sample to indicate the time allocated to school (full-time or part-time) and whether the student is dependent or not. In Appendix D, we present different specifications without these dummy variables but with the sample restricted to full-time dependent students, as shown in Tables D4 and D5.

5 Empirical Results

We now proceed to estimate a multinomial logit model of students' choice of college major, taking subject (iii) - Arts and Humanities - as the reference category. The estimated marginal effects are reported for two model specifications - without controlling for expected earnings (specification 1 in Table 4) and with expected earnings included in the regression (specification 2 in Table 5).

Associated with multinomial logit models is the important assumption of independence of irrelevant alternatives (IIA). In our context of subject choices, the IIA assumption states that an individual's choice between each particular pair of subject groups does not depend on other outcome categories. Looking at the grouping of the five categories of subject fields, as detailed in Section 3 and Appendix A, the faculty groups do not seem to be close substitutes for one other, suggesting that the IIA assumptions are likely to hold in this context. To further examine the validity of our choice of subject groups, we perform Hausman test of the IIA assumption. Test result confirms that the IIA assumption has not been violated.[16]

5.1 The Role of Gender and Social Class

Tables 4 and 5 show evident and consistent gender segregation across disciplines. According to the results in Table 4, the probability of female students choosing Arts and Humanities is 9.5 percentage points higher than male students, *ceteris paribus*. This implies that women are more likely to take up courses that are traditionally considered to be more "feminine". Moreover, these subjects are in general associated with lower earning potential, as suggested by Chevalier (2011), Britton et al. (2016), and Walker and Zhu (2018). In this sense, the results confirm the evidence provided by Campbell et al. (2022), who establish that women tend to choose degree subjects that yield lower monetary returns compared to men.

Remark. The finding that females are more represented in the subjects with lower earning potentials might also be related to their prior academic attainment. That is, under the circumstances that female students on average attain lower exam scores than males, they may select into less selective subjects that yield lower economic returns. While our data does not allow us to control for such prior academic attainment, both education statistics and existing research suggest that this might not be the case in the particular context of our study. According to the aggregate data analyzed in Paper 2 of this thesis, female students have consistently outperformed males in both GCSE outcomes and 'A' level results in England and Wales over the past three decades. Besides, the aforementioned conclusion in Campbell et al. (2022) is reached based on

[16] In Appendix C, we report the Hausman test of the IIA assumption for our baseline estimation (specification 1 based on full sample).

Table 4: Multinomial Logit Model of Students' Subject Choice (Full Sample, Specification 1)

	Science	Social Science	Arts & Humanities	Engineering & Applied Subjects	Professional Subjects
Male	0.022**	0.025*	-0.095***	0.133***	-0.085***
	(0.009)	(0.014)	(0.017)	(0.010)	(0.014)
Age	-0.003***	-0.004***	0.010***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parents Studied in HE	0.001	-0.021	0.003	0.008	0.008
	(0.011)	(0.016)	(0.018)	(0.010)	(0.015)
Social Class I	-0.029*	0.038	-0.045	-0.021	0.057**
	(0.017)	(0.024)	(0.029)	(0.015)	(0.025)
Social Class II	-0.016	-0.038	0.000	-0.029*	0.083***
	(0.017)	(0.026)	(0.029)	(0.015)	(0.025)
Social Class III	-0.028*	-0.004	-0.060**	-0.026*	0.119***
	(0.017)	(0.024)	(0.028)	(0.015)	(0.023)
Social Class IV	-0.038*	0.036	0.095***	-0.090***	-0.003
	(0.020)	(0.027)	(0.031)	(0.023)	(0.028)
Social Class V	-0.007	-0.055**	0.045	-0.026*	0.044*
	(0.016)	(0.025)	(0.028)	(0.015)	(0.024)
Married	-0.013	-0.034	-0.001	0.010	0.037*
	(0.019)	(0.022)	(0.024)	(0.014)	(0.020)
Full-time	0.033	-0.078***	-0.004	-0.075***	0.125***
	(0.020)	(0.024)	(0.027)	(0.015)	(0.021)
Dependent	0.005	-0.018	0.178***	-0.002	-0.163***
	(0.016)	(0.023)	(0.027)	(0.015)	(0.021)
School: State	0.019	-0.007	0.035	0.007	-0.053***
	(0.015)	(0.023)	(0.027)	(0.015)	(0.019)
Institution Type: Oxbridge	0.003	-0.078	0.176***	-0.097*	-0.005
	(0.025)	(0.052)	(0.051)	(0.051)	(0.037)
Institution Type: Post92	-0.045***	0.008	0.134***	0.015	-0.112***
	(0.010)	(0.016)	(0.018)	(0.010)	(0.014)
Institution Type: FEI	-0.062*	0.075**	0.354***	0.082***	-0.449***
	(0.033)	(0.038)	(0.047)	(0.017)	(0.076)
Ethnicity: Black	0.015	0.076**	-0.181***	0.006	0.084***
	(0.026)	(0.034)	(0.045)	(0.022)	(0.031)
Ethnicity: Asian	-0.015	0.080***	-0.199***	0.014	0.120***
	(0.022)	(0.030)	(0.041)	(0.019)	(0.029)
Ethnicity: Other	-0.003	0.029	-0.061	0.010	0.026
	(0.023)	(0.032)	(0.038)	(0.020)	(0.030)
Observations			3,435		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Table 5: Multinomial Logit Model of Students' Subject Choice (Full Sample, Specification 2)

	Science	Social Science	Arts & Humanity	Engineering & Applied Subjects	Professional Subjects
Male	0.064***	0.120***	-0.056***	0.085***	-0.212***
	(0.013)	(0.018)	(0.020)	(0.010)	(0.013)
Age	-0.003***	-0.004***	0.010***	-0.002***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parents Studied in HE	0.002	-0.022	0.002	0.010	0.008
	(0.011)	(0.015)	(0.017)	(0.010)	(0.013)
Social Class I	-0.025	0.050**	-0.035	-0.027*	0.038*
	(0.017)	(0.024)	(0.028)	(0.015)	(0.022)
Social Class II	-0.006	-0.006	0.031	-0.045***	0.026
	(0.017)	(0.025)	(0.029)	(0.015)	(0.022)
Social Class III	-0.028*	0.012	-0.047*	-0.033**	0.096***
	(0.017)	(0.024)	(0.028)	(0.015)	(0.020)
Social Class IV	-0.044**	0.022	0.088***	-0.083***	0.016
	(0.020)	(0.026)	(0.031)	(0.023)	(0.025)
Social Class V	-0.001	-0.027	0.074***	-0.036**	-0.011
	(0.016)	(0.025)	(0.027)	(0.015)	(0.022)
Married	-0.005	-0.017	0.020	0.002	-0.000
	(0.018)	(0.022)	(0.024)	(0.014)	(0.018)
Full-time	0.039*	-0.078***	0.001	-0.071***	0.108***
	(0.020)	(0.024)	(0.027)	(0.015)	(0.019)
Dependent	-0.009	-0.053**	0.147***	0.013	-0.098***
	(0.017)	(0.023)	(0.027)	(0.015)	(0.019)
School: State	0.012	-0.017	0.025	0.008	-0.029
	(0.015)	(0.023)	(0.026)	(0.015)	(0.018)
Institution Type: Oxbridge	0.003	-0.069	0.194***	-0.100**	-0.028
	(0.024)	(0.051)	(0.051)	(0.050)	(0.035)
Institution Type: Post92	-0.047***	0.008	0.137***	0.014	-0.113***
	(0.010)	(0.015)	(0.017)	(0.010)	(0.012)
Institution Type: FEI	-0.080**	0.047	0.329***	0.087***	-0.384***
	(0.032)	(0.035)	(0.043)	(0.018)	(0.062)
Ethnicity: Black	0.010	0.066*	-0.196***	0.006	0.114***
	(0.025)	(0.034)	(0.044)	(0.022)	(0.027)
Ethnicity: Asian	-0.004	0.098***	-0.184***	0.009	0.082***
	(0.022)	(0.030)	(0.041)	(0.019)	(0.027)
Ethnicity: Other	-0.002	0.025	-0.065*	0.012	0.030
	(0.023)	(0.032)	(0.038)	(0.020)	(0.027)
Log Expected Earnings	-0.583***	-1.427***	-0.941***	0.738***	2.214***
	(0.107)	(0.141)	(0.142)	(0.085)	(0.080)
Observations			3,435		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

an analysis that has taken account of prior test grades. Furthermore, Britton et al. (2022) find that university selectivity explains little in the returns to degrees overall, across most of the selectivity distribution. In addition, Owen (2021) finds no strong evidence that female students are more sensitive to grades than males in their choices of college major.

What we can also interpret from the results is that, by contrast, female students tend to avoid subjects such as Science and Engineering which are traditionally largely dominated by males. With other factors hold, the probability of women studying Engineering and Applied Subjects is significantly and greatly lower than men, with a notable gap of 13.3 percentage points, while the probability of women enrolling in Science is 2.2 percentage points lower than their male counterparts. The gender imbalance suggests that women are overall underrepresented in the "STEM" degree fields. This finding is supported by the evidence in the UK, as has been discussed in great detail in the existing literature (e.g., Britton et al., 2022). Such variation by gender in STEM degree fields has also been found in other countries such as the US (Zafar, 2013; Porter and Serra, 2020) and Canada (Card and Payne, 2017).[17]

Furthermore, comparing the results in Tables 4 and 5, we note that when expected earnings are controlled for, the marginal effect of the gender variable falls from 0.133 to 0.085 in the category of Engineering & Applied Subjects. This effectively means that the male bias towards the subject could arise from their desire for the high earnings associated with the discipline, but not all of it. Other factors could also come into play. In particular, an individual's perceptions about the occupation - and subsequently her personal preference for the subject - could be influenced by non-pecuniary considerations such as the social notion that men typically possess stronger aptitude for the field, and the cultural expectation that engineering is a male-dominant profession. Therefore, male students are overall more interested in engineering and may thus select into the subject. On the other hand, they are also motivated to learn more about the major, and hence may be better-informed about the labor market prospects associated with the field. As such, field-specific potential earning is not the only force that drives them to choose engineering. So when we account for the expectation of future earnings, men

[17] In particular, Card and Payne (2016) show a gender gap of 13 percentage points in the probability of studying STEM subjects, which is similar to our estimated results in terms of the gender difference in Engineering and Applied Subjects.

are still more likely to choose this subject than women, but the gender gap appears to be attenuated.

Consistent with the descriptive statistics as shown in Table 3, female students are more liable to choose Professional Studies. Specifically, the probability of women choosing Professional Subjects is 8.5 percentage points higher than men. This pattern is not surprising though. As explained in Section 3, we define the Professional programs to include Medicine and Dentistry, Subjects Allied to Medicine, Veterinary Science, and Law. In fact, a higher proportion of women study Subjects Allied to Medicine than men, which is consistent with the evidence that women are more likely to take up health-related programs (Britton et al., 2020).

Turning now to the role of social classes, a socio-economic gap is found in the choice of Arts and Humanities, and the difference becomes more evident when we control for expected earnings and focus on full-time and dependent students, as shown in Table D5. Compared with the lowest SES group of individuals, students of higher social class seem to opt for Arts and Humanities as their college major. By contrast, we observe that individuals from higher social class backgrounds have a lower propensity to enroll in Science and Engineering programs. Put differently, economically disadvantaged students tend to enroll in the relatively "practical" programs which allow them to secure employment more quickly upon graduation and receive relatively higher starting salaries.

Another result that we can interpret from Table 4 is that children of the professional class - including social class I (managers and administrators), social class II (professional occupations), and social class III (associate professional occupations) - especially prefer Professional Subjects, as compared to the lowest SES group. All the corresponding predicted marginal effects are positive and statistically significant. Similar patterns are observed in Table 5 where individuals' expected wage of future employment is controlled for. However, the effect weakens in magnitude and becomes insignificant for social class II (professional occupations). In addition, when we focus on full-time dependent students, as shown in Table D4, only the positive marginal effect for Social Class II (professional occupations) remains statistically significant.

Remark. As explained in Section 3, we categorize Subjects Allied to Medicine as a professional subject due to the lack of specific information on its classification. In view of this data limitation, we re-run the regressions by excluding from the sample those individuals studying for Subjects Allied to Medicine. New results support that children from social class II (professional occupations) opt for Professional Subjects, with the marginal effects remaining statistically significant and positive (0.060 and significant at the level of significance of 1% for the full sample; 0.057 and significant at the level of 5% for the sample of full-time dependent students). However, the impacts also weaken when we control for expected earnings, with the marginal effects being insignificant.

To further explore how subject choices vary across gender and social classes, we also include in the models the interactions of these two variables. The marginal effects of the crossed terms are presented in Table 6. The last three columns in the upper panel suggest that, compared to their female counterparts, males from all social classes overall tend to opt for Engineering & Applied Subjects, whereas the opposite is the case for Arts & Humanities and Professional subjects. When expected earnings are accounted for, as shown in the lower panel, the gender gaps get narrower in the case of Arts & Humanities as well as Engineering & Applied Subjects, while the difference across gender becomes larger for Professional Subjects. These results confirm the patterns observed in Tables 4 and 5. Moreover, across the social classes, the marginal effects are the largest in size for boys from Social Class V (manufacturing crafts and personal and protective services) choosing Arts & Humanities, from the lowest SES group choosing Engineering and Applied Subjects, and from Social Class III (associate professional and technical occupations) choosing Professional Subjects. Importantly, female students of the lowest SES group appear to be least inclined to select Engineering & Applied Subjects, compared with their male counterparts of the same social class or females in other higher SES groups.

When it comes to Science, the gender differences in the probability of selecting the subject are mostly insignificant in Specification 1, across all the social classes except for Social Class IV. Whereas when we control for expected earnings as in Specification 2, most of the marginal effects become statistically significant and the gender gaps are widened, with males from Social Class IV liking the subject most.

Finally, looking at the gender gap in choosing Social Science, the evidence appears to be mixed. According to the upper panel, boys from social classes I, II, III, and V seem to prefer the subject; and among these groups, the marginal effect appears only statistically significant, and largest in size, for boys from social class III. This preference remains strongest compared with other socio-economic groups when expected earnings are taken account of; besides, all the marginal effects are positive and mostly significant, with the gender gaps widening for Social Classes I, II, III, and V.

Table 6: Marginal Effects of Gender by Social Class

	Science	Social Science	Arts & Humanities	Engineering & Applied Subjects	Professional Subjects
Full Sample, Specification 1					
Gender × Social Class					
Male × Social Class I	0.0001	0.003	-0.128***	0.196***	-0.071**
Male × Social Class II	0.026	0.030	-0.128***	0.110**	-0.038
Male × Social Class III	0.032	0.129***	-0.103***	0.137***	-0.196***
Male × Social Class IV	0.072**	-0.033	-0.049	0.046*	-0.036
Male × Social Class V	0.023	0.032	-0.162***	0.180*	-0.073*
Male × Social Class VI	0.005	-0.070**	-0.061	0.215***	-0.089***
Observations			3,435		
Full Sample, Specification 2					
Gender × Social Class					
Male × Social Class I	0.041	0.134***	-0.085**	0.119**	-0.209***
Male × Social Class II	0.079**	0.134***	-0.093**	0.044*	-0.164***
Male × Social Class III	0.065**	0.227***	-0.068*	0.077**	-0.301***
Male × Social Class IV	0.100**	0.053	-0.012	0.023	-0.164***
Male × Social Class V	0.066	0.097*	-0.147**	0.124*	-0.140***
Male × Social Class VI	0.059*	0.031	-0.008	0.129***	-0.209***
Observations			3,435		

Notes:
The control variables of Specification 1 include the same set of control variables as in Table 4 and the crossed terms of gender and social class (*Male × Social Class*).
The control variables of Specification 2 include the same set of control variables as in Table 5 (with expected earnings added) and the crossed terms of gender and social class (*Male × Social Class*).
Average marginal effects of the crossed terms (*Male × Social Class*) are reported in this table.
Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

5.2 Implications for Expected Earnings

Turning now to the average marginal effects of expected wage, it is not surprising that the probability of choosing Engineering (and Applied Subjects) or Professional Subjects - two of the most lucrative degree fields - increases with students' expected future earnings, consistent with the expectation that the utility of a college major increases with the expected earnings. More specifically, if the expected earnings increased by 1%, *ceteris paribus*, the likelihood of studying for Engineering and Applied Subjects would increase by 0.74 percentage points. And the marginal effect triples for Professional Subjects, suggesting a notable rise of 2.21 percentage points in the probability of choosing this degree field when expected earnings increase by 1%. Both effects are highly significant and are substantially greater than the marginal effects suggested by Boudarbat and Montmarquette (2009). For instance, the authors find that the marginal effects of expected log initial earnings in the field of "agricultural and biological sciences" on the probability of selecting this college major are only 0.048 and 0.053 for females and males respectively, while the marginal effects in the category of "commerce and business" are 0.085 and 0.166 for females and males respectively. It should be noted that, however, these estimates are not directly comparable with our results as they are based on a sample of students whose parents do not have a university degree. Nonetheless, these estimates still serve as a benchmark for our study, and the difference in the marginal effects suggests that our results could be overestimated, which will be further discussed below.

By contrast, expected wages seem to be negatively correlated with college students' preferences for the other three subject groups. If students' expected earnings increased by 1%, the probability of their opting for Science and Arts & Humanities would drop by 0.58 and 0.94 percentage points, respectively. The scale of the negative effect on the odds of selecting Social Science is larger, with the probability dropping by 1.43 percentage points in response to a 1% increase in the expected earnings. All the marginal effects are statistically significant at the 1 percent level.

The findings seem plausible given the heterogeneity of individuals' considerations concerning employment prospects. Boudarbat and Montmarquette (2009) provide related descriptive evidence of this heterogeneity, suggesting that graduates from "fine arts and humanities" courses attach less importance to the income prospects in their selection into their college majors, in contrast to graduates with a major in "commerce and business" who regard the pecuniary considerations as a dominant determinant.

Moreover, many studies reveal that pecuniary returns explain little of the variation in subject choices (see, e.g., Zafar, 2013; Stinebrickner and Stinebrickner, 2014). Instead, some factors other than monetary returns have been found to play a dominant role in determining fields of study, such as the preferences for particular college majors (Arcidiacono, 2004), the consumption value of schooling which is associated with abilities and schooling (Beffy et al., 2012; Stinebrickner and Stinebrickner, 2014), unobserved "tastes" such as enjoyability of coursework (Zafar, 2013; Wiswall and Zafar, 2015), as well as job preferences - flexibility and stability of future work - which are associated with college majors (Wiswall and Zafar, 2018). Considering all these non-pecuniary factors, prospective HE students who are interested in a particular discipline may select into this college major. Besides, they might have great incentive to learn more about the subject, and thus get better-informed about the potential earnings in the associated professions. Consequently, providing them with earnings information might not predominantly influence their choice of field of study, because expected earnings wouldn't affect their non-pecuniary considerations for the subject. This is supported by the evidence, as presented earlier in Section 5.1, that when expected earnings are controlled for, the gender gap shrinks in the probability of choosing Engineering and Applied Subjects.

Therefore, taking account of these non-pecuniary factors would be necessary to analyze the effect of earnings expectations. Without doing so, as Wiswall and Zafar (2015) point out, the empirical study would "inflate the role of earnings in college major choices." In this sense, our evidence regarding the effect of expected earnings could have been obscured due to the lack of data on non-pecuniary attributes and the estimated marginal effect might be subject to upward bias. This partly explains why these marginal effects are considerably larger in magnitude than those suggested by Boudarbat and Montmarquette (2009).

Furthermore, it should be noted that in this paper, it is the exogenous income data of past graduates that we use to proxy the expected earnings of the cohort in study. An underlying assumption is that prospective HE students would know about the earning outcomes of earlier cohorts, by subject and by gender, so that they could form their beliefs about future earnings. In Section 3.3.1, we provide some evidence to support our argument that students are informed about past graduates' salaries. However, we are uncertain of the extent to which they would make correct expectations based on the information. Practically we are unable to verify the assumption with the data being used. Whereas the evidence on whether college students form unbiased earning expectations remains mixed so far in the literature (see, eg., Arcidiacono et al., 2012; Wiswall and Zafar, 2015; Hastings et al., 2016; Conlon, 2021). As such, we must acknowledge that this could be a potential drawback of our analysis; and more caution should be exercised in interpreting any results that draw upon the assumption. Nonetheless, it would be particularly interesting to probe into this issue further in our future work, so as to better understand not only students' expectation of earnings but also the underlying role it plays in affecting their subject choices.

5.3 Effects of Other Variables

Some other factors also appear to affect students' choices of field. Compared with white students, black students and Asian students seem to opt for Social Science and Professional Subjects. On the other hand, they are less likely to choose Arts and Humanities as their degree subjects. Other plausible evidence includes that students from state schools are less likely to study Professional Subjects as compared to students from independent or private schools; and married students are more liable to take up courses in Professional Subjects. A noteworthy finding is that parental education, in this paper measured by whether parents studied in HE or not, appears to have no significant effects on individuals' fields of study in all the specifications. The evidence on the impact of institution types is somewhat mixed. Compared to their counterpart peers studying in pre-1992 HEIs, students from Oxbridge, post-1992 HEIs, and FEIs tend to take up courses in Arts and Humanities, while post-1992 HEIs and FEIs students are less liable to enroll in Science or Professional Programs.

Remark. Unlike some countries where the majority of college students declare a major after entering universities, in the UK the application for an undergraduate course is typically a combination of subject and institution choices, namely at the 'degree level' as discussed by Britton et al. (2022). Hence, a promising setting is to study prospective HE students' subject choice interacted with their institution choice. However, in the absence of a large-scale data set, the type of institution enters the model as a control variable instead, which we think captures the focus of this paper: students' choice of college major. Another consideration is that, as suggested by Campbell et al. (2022), it is the degree subject choices, rather than the institutions attended, that explain almost the entire earnings difference by gender. Nonetheless, to establish the robustness of the preceding findings, we conduct additional regressions by excluding the institution type from the models. Appendix E provides evidence that our main results hold in robustness checks: the sign and the size of the key parameters in Tables E6 to E9 are comparable to those of the corresponding parameters in our main results presented in Tables 4, 5, D4, and D5.

6 Conclusion

In this study, we examine the determinants of subject choice at the undergraduate level in England and Wales, with an emphasis on the role of gender, social class, and expected earnings. Above all, we identify significant gender gaps in the choice of college majors. Specifically, STEM majors, including Science and Engineering & Applied Subjects, are persistently segregated by gender, with women more inclined to avoid these fields. On the contrary, females seem to prefer Arts & Humanities. Besides, in examining the marginal effect of the interaction of gender and social class, we find that female students of the lowest SES group are least inclined to choose Engineering & Applied Subjects as their field of study, compared with their male counterparts of the same social class or females in other higher SES groups. Further, we observe that the impacts of expected earnings appear to vary among subject choices. The expectation of earnings is positively correlated with the probability of choosing subjects that yield higher payoffs; in contrast, it is negatively correlated with the likelihood of selecting the less lucrative fields.

From a policy perspective, our findings suggest that there should be field-specific measures to motivate students' participation in a particular course. Take Engineering and Applied Subjects, for example. Engineering has been a field traditionally segregated by gender, in which women are significantly less represented. The past two decades have seen women overtaking men among college enrolments. However, according to HESA's aggregate statistics, for a long period of time, female students account for only less than one quarter of the student population, despite that engineering is among the more lucrative occupations. The underrepresentation of women in engineering is consistent with the evidence provided by this study. In particular, we find that there is a substantial gender difference in the choice of Engineering & Applied Subjects. Further, this gender imbalance appears largest in magnitude among all the gender gaps in the five categories of subject choices.

The prominent force behind the gender imbalance in engineering could be the unobserved factors other than economic returns, such as unobserved "tastes" and future job preferences. In particular, female students generally assume that engineering is a subject that is difficult to navigate and an occupation that is persistently dominated by men, and thus they may be deterred from choosing the related college majors. Therefore, to address the lack of female representation in the field, it would be crucial to provide prospective students with detailed program-specific information, focusing on the breadth of the curriculum, the influence of this field on our lives, as well as the future career prospects. For example, global climate change is a matter for heated debate nowadays and has attracted widespread public concerns. Emphasizing the crucial role that engineering plays in tackling climate change might help to arouse female students' interest in pursuing further education in the field engineering. Additionally, it would also be necessary to stress that these courses can help develop their solid background and transferable skills, which open up a gateway to an inspiring future career. Furthermore, female role model interventions, inexpensive but efficient, could also matter significantly in affecting women's self-selection into a specific field, as demonstrated by Porter and Serra (2020). Exposure to counter-stereotypical female role models, past and present, could contribute to dispelling girls' misperceptions that engineering is just a field for males, and raising their expectations of success in the future as an engineer.

Finally, our work also sheds some light on policy concerns regarding HE finance. Faced with funding cuts and inflation, some HEIs have called for further increasing tuition fees, otherwise they would consider cutting back on places for some STEM courses due to the rising costs incurred for supplying these courses. However, as our study suggests, female students of the lowest SES group are least inclined to choose Engineering & Applied Subjects, an important STEM major, as their field of study, compared with their male counterparts of the same social class or females in other higher SES groups. Were tuition fees further increased, it would be these economically disadvantaged female students - who we expect to be on the margin of choosing engineering programs - that are most likely inhibited from HE participation in this degree subject, which could further impair social mobility in the long run.

Furthermore, our analysis also indicates that girls from lower SES groups, especially Social Class V, are strongly inclined to choose Arts and Humanities which, in general, is associated with lower life-time earnings. If this pattern persists, we might imagine that they will consistently earn less in the workforce. Due to the income-contingent nature of the present student loan repayment system in the UK, students who have lower lifetime earnings will make less contribution to their loan repayment over lifetime. As a result, in the long run there could an adverse impact on the efficiencies and equities of the HE finance system.

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Appendix A Key Variables: Definitions

Faculty Group

(i) Science - Biological Sciences, Physical Sciences (including Chemistry and Physics), Mathematical Sciences, Sports Science Studies

(ii) Social Science - Architecture, Building, and Planning, Social Studies (including Economics, Politics, and Geography), Business and Administrative Studies, Psychology, Counsell, Criminol

(iii) Arts and Humanities - Languages (including Classics), Education, Mass Communications and Documentation, Historical and Philosophical Studies, English, Creative Arts and Design, Music, Combined

(iv) Engineering and Applied Subjects - Agriculture and related subjects, Computer Sciences, Engineering and Technology

(v) Professional Subjects - Medicine and Dentistry, Subjects allied to Medicine, Veterinary Science, Law

Social Class Group

Social Class I - Managers and Administrators

Social Class II - Professional Occupations

Social Class III - Associate Professional and Technical Occupations

Social Class IV - Clerical Occupations

Social Class V - Manufacturing crafts; Personal and Protective Services

Social Class VI - Sales Occupations; Plant and Machine Operatives; Others

State (Type of School)

state=1: state school (including grant-maintained schools)

state=0: other (e.g., independent or private schools)

Married/Joint

Whether married or joint financial responsibility

Appendix B Expected Earnings

Endogeneity problems could arise from using students' own expected wages upon graduation or five years after graduation, which is the only information we can infer from SIES 2004/05 regarding expected earnings. An alternative is to use exogenous data on wage prospects in different subjects. Assuming that students base their expectation of future earnings on the observed graduate income of previous cohorts, we calculate the annual earnings of the preceding cohorts of graduates aged 21 to 25 as a proxy for the expected earnings of the cohort in question. Using data from Labour Force Survey (LFS) (1993-2003), we compute SOC-specific median earnings for each of the following age groups: age 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, and 60 and above.[18] Table B1 shows the median annual earnings by age group and by SOC category (1-digit level major occupation codes).

As the LFS does not contain data related to college majors, we refer to HESA's annual publication of First Destinations of Students Leaving Higher Education Institutions for relevant information. Based on the HESA data, we compute the distribution of graduates' first destinations by SOC group (1-digit level major occupation codes), within each of the twenty-six subject groups. The calculated weights are summarised in Table B2 where each row represents, for a given field of study, the proportion of graduates who acquire an occupation that falls into each of the nine SOC categories which are the same as those in Table B1.

We are then able to calculate the weighted annual earnings by subject and by faculty group, as shown in Table B3. Specifically, Table B3 is calculated by multiplying the two corresponding rows in Tables B1 and B2. For instance, the first cell is obtained by multiplying the first row in Table B2 with the first row (transposed) in Table B1. In our estimation, we employ the calculated data of median earnings of the 21 to 25 age group, by gender and across twenty-six subject groups.

[18]Data on earnings is converted to 2006 price.

Table B1: Median Annual Earnings by SOC and Age (2006 Price, £)

		SOC1	SOC2	SOC3	SOC4	SOC5	SOC6	SOC7	SOC8	SOC9
Age Groups	21∼25	18381.74	18796.21	17561.66	14092.67	17384.32	15688.26	15174.02	14762.00	13900.71
	26∼30	25799.68	24754.08	21813.00	15332.01	20101.50	20392.81	22276.95	16788.65	16205.79
	31∼35	34530.79	29357.41	25428.07	17265.40	24991.15	25533.22	27683.77	19158.18	14504.26
	36∼40	37727.26	31392.28	25918.25	17561.66	23997.03	28307.88	34829.01	20968.11	14368.63
	41∼45	39785.16	31328.00	25428.07	16220.59	25181.30	22609.54	29678.29	22364.45	18259.20
	46∼50	43119.11	32457.79	26366.24	16482.29	20885.33	21642.33	26178.58	19738.45	18591.57
	51∼55	45163.11	33782.84	26592.25	16237.44	22714.30	20070.01	37988.93	20100.63	19860.64
	56∼60	43132.32	34067.49	26545.18	15478.24	23373.73	19497.00	23812.90	16766.76	16803.91
	>60	34829.01	33311.34	25181.30	14945.60	17210.43	17296.75	18591.57	13581.50	16042.44
	Total	37727.26	31328.00	25428.07	15332.01	22714.30	21642.33	23812.90	19158.18	14504.26

Source: Authors' calculation based on LFS

Table B2: Weights on First Destinations of Graduates (%)

		SOC1	SOC2	SOC3	SOC4	SOC5	SOC6	SOC7	SOC8	SOC9
	1 Medicine and Dentistry	0.184	99.378	0.173	0.096	0.011	0.070	0.066	0.022	0.004
	2 Subjects Allied to Medicine	1.828	13.490	78.337	2.340	0.148	1.584	1.529	0.137	0.222
	3 Biological Sciences	14.254	22.640	20.662	18.058	0.994	7.980	9.835	1.523	2.411
	4 Veterinary Science	0.695	98.307	0.521	0.087	0.043	0.217	0.391	0.043	0.130
	5 Agriculture and Related	30.318	17.958	11.091	9.471	4.603	4.575	7.530	1.695	9.623
	6 Physical Sciences (incl Chemistry and Physics)	15.435	24.282	18.885	19.182	1.440	5.471	8.653	1.767	2.883
	7 Mathematical Sciences	12.861	40.017	18.469	18.130	0.501	2.453	4.637	0.586	1.219
	8 Computer Sciences	11.115	25.696	45.196	8.563	2.376	1.147	3.128	0.445	0.768
	9 Engineering and Technology	12.226	52.828	14.682	5.619	3.539	1.786	4.921	1.160	1.541
	10 Architecture, Building and Planning	16.130	35.347	32.091	5.612	1.923	1.694	3.641	0.711	1.621
	11 Social Studies (incl Economics, Politics and Geography)	19.979	23.010	16.059	21.825	0.477	7.186	7.653	0.731	1.616
	12 Law	19.037	19.117	19.085	25.913	0.456	5.373	7.468	0.552	1.351
Subjects	13 Business and Administrative Studies	35.095	14.536	10.366	24.484	0.430	3.293	8.440	0.577	1.333
	14 Mass Comms and Documentation	25.694	4.967	26.514	22.766	0.935	4.752	10.049	0.698	1.824
	15 Languages incl Classics	26.749	8.582	14.799	29.361	0.454	5.679	10.430	0.531	1.650
	16 Historical and Philosophical Studies	20.828	11.910	13.133	28.449	0.853	7.964	11.608	1.032	2.460
	17 Creative Arts and Design	11.340	5.332	38.621	12.317	3.552	7.562	13.372	1.173	2.362
	18 Education	1.878	90.426	1.975	1.950	0.131	1.952	1.110	0.160	0.232
	19 Combined	22.641	15.022	17.419	23.208	0.815	6.953	9.764	0.848	1.714
	21 Counselling	19.979	23.010	16.059	21.825	0.477	7.186	7.653	0.731	1.616
	22 Music Studies	12.464	18.332	25.368	19.550	1.099	6.849	10.249	0.744	1.251
	23 Psychology	16.497	16.589	16.502	22.929	0.400	15.057	8.854	0.512	1.337
	24 English Literature/Language etc	21.309	6.096	16.702	30.086	0.590	8.047	13.019	0.620	1.872
	25 Criminology/Criminal Justice Studies	19.979	23.010	16.059	21.825	0.477	7.186	7.653	0.731	1.616
	26 Sports Science Studies	25.391	14.833	16.540	15.897	1.305	11.441	9.615	1.505	2.208

Source: Authors' calculation based on First Destinations of Students Leaving Higher Education Institutions

Table B3: Median Annual Earnings by Subject and Age Group (2006 Price, £)

		Age Groups								
		21∼25	26∼30	31∼35	36∼40	41∼45	46∼50	51∼55	56∼60	>60
Subjects	1 Medicine and Dentistry	18783.69	24735.52	29342.57	31378.76	31309.71	32436.45	33764.23	34031.98	33255.96
	2 Subjects Allied to Medicine	17516.21	22009.97	25838.57	26716.36	26173.20	27049.54	27598.69	27309.07	25844.49
	3 Biological Sciences	16526.18	21222.10	25590.60	27600.30	26701.14	27177.17	28861.42	26931.67	24381.65
	4 Veterinary Science	18834.78	24809.56	29449.34	31508.89	31429.96	32550.55	33913.67	34116.70	33277.87
	5 Agriculture and Related	16479.45	21518.57	26320.22	28374.01	28609.05	29433.52	31322.88	29267.20	25507.48
	6 Physical Sciences (incl Chemistry and Physics)	16504.40	21150.07	25481.41	27402.14	26750.81	27312.70	28950.92	27156.52	24592.36
	7 Mathematical Sciences	17115.83	21962.23	26339.90	28112.87	27701.07	28583.78	29910.04	28891.60	26817.74
	8 Computer Sciences	17256.90	22007.30	26301.76	27665.56	27379.16	28254.69	29309.76	28598.23	26463.99
	9 Engineering and Technology	17574.75	22911.62	27582.47	29521.73	29354.89	30144.93	31755.83	30838.10	28630.31
	10 Architecture, Building and Planning	17518.07	22696.66	27367.94	29075.43	28963.80	29977.00	31295.52	30424.47	27969.42
	11 Social Studies (incl Economics, Politics and Geography)	16597.35	21350.13	25952.53	27955.26	27255.28	28017.46	29536.34	27826.14	25035.30
	12 Law	16420.92	20942.54	25368.03	27222.19	26535.45	27290.10	28737.20	27053.17	24365.47
	13 Business and Administrative Studies	16596.48	21618.46	26837.51	29077.25	28853.56	29992.76	31838.07	29703.51	25839.62
	14 Mass Comms and Documentation	16310.67	20940.84	25630.31	27600.84	26994.51	27765.48	29515.55	27297.94	23921.08
	15 Languages incl Classics	16127.07	20684.78	25380.57	27475.43	26770.24	27526.75	29322.47	26997.56	23626.35
	16 Historical and Philosophical Studies	16036.24	20501.74	24954.67	27068.72	26112.28	26600.02	28439.92	26033.47	22997.81
	17 Creative Arts and Design	15939.21	20372.88	24515.68	26360.41	25266.58	25382.80	27301.90	24948.31	22235.25
	18 Education	18516.94	24334.68	28936.99	30987.28	30776.39	31817.46	33160.06	33183.47	32190.58
	19 Combined	16392.67	21094.85	25757.77	27836.83	27085.52	27773.68	29501.62	27400.93	24293.07
	21 Counselling	16597.35	21350.13	25952.53	27955.26	27255.28	28017.46	29536.34	27826.14	25035.30
	22 Music Studies	16051.65	20513.20	24696.69	26573.59	25585.70	26009.99	27658.52	25749.32	23338.85
	23 Psychology	16316.57	20903.67	25409.17	27476.74	26167.08	26637.63	28010.83	26144.51	23457.38
	24 English Literature/Language etc	15928.07	20329.94	24785.80	26918.32	25826.93	26272.83	28201.09	25583.75	22453.08
	25 Criminology/Criminal Justice Studies	16597.35	21350.13	25952.53	27955.26	27255.28	28017.46	29536.34	27826.14	25035.30
	26 Sports Science Studies	16610.27	21615.75	26590.67	28848.03	28041.96	28717.46	30444.43	28304.93	24875.26

Source: Authors' calculation based on Tables B1 and B2

Appendix C Hausman Test of IIA Assumption

	chi2	df	P>chi2
1	1.229	57	1.000
2	11.564	57	1.000
3	6.456	57	1.000
4	-0.611	56	.
5	4.946	57	1.000

Notes:

The p values of chi2 indicate that we can not reject the null hypothesis of independent alternatives: "Odds (Outcome-J vs Outcome-K) are independent of other alternatives."

According to Hausman and McFadden (1984), the negative value of chi2 in row 4 provides evidence that the IIA assumption is validated.

Appendix D Results for Full-time Dependent Students

Regarding students' socio-economic status, the survey provides separate information for three different sub-groups, based on full-time independent students' last paid job prior to their course of study, part-time students' current or last paid job, and for full-time dependent students the occupation of the family's main income earner. On account of this difference, in Section 5 we include dummy variables for full-time and dependent students in our main regression on the full sample. In this appendix, we present a different setting without these dummy variables, while the sample is restricted to full-time dependent students.

Table D4: Multinomial Logit Model of Students' Subject Choice (FT Dependent Students, Specification 1)

	Science	Social Science	Arts & Humanities	Engineering & Applied Subjects	Professional Subjects
Male	0.036**	0.023	-0.123***	0.121***	-0.057***
	(0.014)	(0.019)	(0.022)	(0.013)	(0.018)
Age	-0.020***	-0.004	-0.007	0.004	0.027***
	(0.005)	(0.006)	(0.007)	(0.003)	(0.005)
Parents Studied in HE	0.007	-0.008	-0.020	-0.003	0.025
	(0.017)	(0.022)	(0.024)	(0.013)	(0.020)
Social Class I	-0.055**	-0.004	0.041	-0.026	0.044
	(0.025)	(0.032)	(0.037)	(0.017)	(0.030)
Social Class II	-0.032	-0.037	0.058	-0.058***	0.070**
	(0.026)	(0.035)	(0.039)	(0.020)	(0.031)
Social Class III	-0.036	0.021	0.082**	-0.069***	0.002
	(0.027)	(0.035)	(0.039)	(0.022)	(0.034)
Social Class IV	-0.071**	-0.012	0.144***	-0.096***	0.036
	(0.035)	(0.041)	(0.045)	(0.030)	(0.038)
Social Class V	0.004	-0.022	0.083**	-0.041**	-0.023
	(0.025)	(0.035)	(0.039)	(0.019)	(0.034)
Married	0.034	0.081	-0.130**	0.003	0.011
	(0.043)	(0.050)	(0.062)	(0.036)	(0.047)
School: State	0.027	0.001	0.020	0.012	-0.060***
	(0.023)	(0.030)	(0.033)	(0.018)	(0.022)
Institution Type: Oxbridge	0.004	-0.126**	0.224***	-0.091*	-0.011
	(0.033)	(0.058)	(0.053)	(0.047)	(0.036)
Institution Type: Post92	-0.060***	-0.020	0.203***	-0.012	-0.111***
	(0.015)	(0.020)	(0.022)	(0.012)	(0.017)
Institution Type: FEI	-0.066	0.066	0.430***	-0.020	-0.409***
	(0.052)	(0.064)	(0.077)	(0.037)	(0.136)
Ethnicity: Black	-0.179*	0.113*	-0.093	0.038	0.121**
	(0.104)	(0.060)	(0.078)	(0.034)	(0.052)
Ethnicity: Asian	-0.016	0.100***	-0.233***	0.023	0.126***
	(0.031)	(0.035)	(0.048)	(0.019)	(0.029)
Ethnicity: Other	0.007	-0.052	0.004	0.015	0.027
	(0.034)	(0.049)	(0.050)	(0.026)	(0.036)
Observations			1,946		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Table D5: Multinomial Logit Model of Students' Subject Choice (FT Dependent Students, Specification 2)

	Science	Social Science	Arts & Humanity	Engineering & Applied Subjects	Professional Subjects
Male	0.053***	0.063**	0.008	0.061***	-0.185***
	(0.020)	(0.025)	(0.028)	(0.012)	(0.015)
Age	-0.015***	0.004	0.007	-0.001	0.005
	(0.005)	(0.006)	(0.006)	(0.003)	(0.004)
Parents Studied in HE	0.008	-0.007	-0.027	-0.001	0.027
	(0.017)	(0.022)	(0.023)	(0.013)	(0.017)
Social Class I	-0.051**	0.003	0.057	-0.031*	0.022
	(0.025)	(0.032)	(0.035)	(0.016)	(0.026)
Social Class II	-0.025	-0.019	0.082**	-0.068***	0.030
	(0.026)	(0.035)	(0.037)	(0.020)	(0.027)
Social Class III	-0.038	0.018	0.074**	-0.063***	0.008
	(0.027)	(0.034)	(0.038)	(0.021)	(0.029)
Social Class IV	-0.072**	-0.010	0.131***	-0.088***	0.038
	(0.035)	(0.041)	(0.044)	(0.029)	(0.033)
Social Class V	0.002	-0.029	0.076**	-0.035*	-0.014
	(0.025)	(0.034)	(0.036)	(0.019)	(0.029)
Married	0.042	0.093*	-0.118**	0.002	-0.019
	(0.043)	(0.050)	(0.060)	(0.035)	(0.042)
School: State	0.022	-0.009	0.009	0.014	-0.035*
	(0.023)	(0.029)	(0.032)	(0.018)	(0.020)
Institution Type: Oxbridge	0.009	-0.114**	0.240***	-0.096**	-0.039
	(0.032)	(0.057)	(0.053)	(0.045)	(0.036)
Institution Type: Post92	-0.062***	-0.030	0.192***	-0.007	-0.094***
	(0.015)	(0.020)	(0.022)	(0.012)	(0.016)
Institution Type: FEI	-0.086*	0.020	0.331***	0.011	-0.276***
	(0.050)	(0.058)	(0.063)	(0.038)	(0.106)
Ethnicity: Black	-0.179*	0.107*	-0.114	0.037	0.148***
	(0.103)	(0.060)	(0.077)	(0.033)	(0.041)
Ethnicity: Asian	-0.006	0.115***	-0.215***	0.017	0.090***
	(0.031)	(0.035)	(0.046)	(0.018)	(0.026)
Ethnicity: Other	0.010	-0.053	-0.006	0.018	0.031
	(0.034)	(0.048)	(0.049)	(0.025)	(0.033)
Log Expected Earnings	-0.316**	-0.706***	-1.941***	0.899***	2.065***
	(0.150)	(0.191)	(0.202)	(0.105)	(0.099)
Observations			1,946		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Appendix E Robustness Check

As discussed in Section 5.3, the ideal setting to study prospective HE students' subject choice is to consider the combination of their subject and institution choices. However, in the absence of a large-scale data set, and given that the focus of our study is students' choice of college major, the type of institution enters the model as a control variable instead, which we think captures the focus of this paper. The main results are presented in Tables 4, 5, D4, and D5. Nonetheless, we realize that this may be considered a potential drawback of the model specification; and we re-run the regressions by excluding the institution type to establish the robustness of the main results. As shown in this appendix, our main results hold in robustness checks: the sign and the size of the key parameters in the following tables (Tables E6 to E9) are comparable to those in our main results.

Table E6: Multinomial Logit Model of Students' Subject Choice (Robustness Check, Full Sample, Specification 1)

	Science	Social Science	Arts & Humanities	Engineering & Applied Subjects	Professional Subjects
Male	0.024**	0.023*	-0.101***	0.134***	-0.080***
	(0.009)	(0.014)	(0.017)	(0.010)	(0.015)
Age	-0.003**	-0.004***	0.010***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parents Studied in HE	0.006	-0.023	-0.006	0.006	0.017
	(0.011)	(0.016)	(0.018)	(0.010)	(0.015)
Social Class I	-0.023	0.038	-0.059**	-0.022	0.066***
	(0.017)	(0.024)	(0.029)	(0.015)	(0.025)
Social Class II	-0.008	-0.042*	-0.012	-0.032**	0.094***
	(0.017)	(0.026)	(0.029)	(0.015)	(0.025)
Social Class III	-0.024	-0.004	-0.069**	-0.028*	0.125***
	(0.017)	(0.024)	(0.028)	(0.015)	(0.023)
Social Class IV	-0.033	0.037	0.082***	-0.092***	0.006
	(0.021)	(0.027)	(0.032)	(0.023)	(0.029)
Social Class V	-0.005	-0.055**	0.043	-0.024	0.042*
	(0.016)	(0.026)	(0.028)	(0.015)	(0.025)
Married	-0.019	-0.033	0.015	0.011	0.026
	(0.019)	(0.022)	(0.025)	(0.014)	(0.020)
Full-time	0.038*	-0.079***	-0.003	-0.083***	0.127***
	(0.020)	(0.024)	(0.028)	(0.016)	(0.021)
Dependent	0.007	-0.019	0.165***	-0.005	-0.149***
	(0.017)	(0.023)	(0.027)	(0.015)	(0.021)
School: State	0.009	0.001	0.054**	0.016	-0.080***
	(0.015)	(0.023)	(0.026)	(0.015)	(0.019)
Ethnicity: Black	0.008	0.081**	-0.166***	0.006	0.072**
	(0.026)	(0.034)	(0.045)	(0.023)	(0.032)
Ethnicity: Asian	-0.018	0.080***	-0.191***	0.013	0.115***
	(0.022)	(0.030)	(0.042)	(0.019)	(0.029)
Ethnicity: Other	-0.002	0.028	-0.059	0.006	0.027
	(0.023)	(0.032)	(0.039)	(0.020)	(0.030)
Observations			3,435		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Table E7: Multinomial Logit Model of Students' Subject Choice (Robustness Check, Full Sample, Specification 2)

	Science	Social Science	Arts & Humanity	Engineering & Applied Subjects	Professional Subjects
Male	0.063***	0.120***	-0.062***	0.086***	-0.207***
	(0.013)	(0.018)	(0.020)	(0.010)	(0.013)
Age	-0.003**	-0.004***	0.010***	-0.002***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parents Studied in HE	0.006	-0.023	-0.007	0.006	0.018
	(0.011)	(0.015)	(0.018)	(0.010)	(0.013)
Social Class I	-0.019	0.050**	-0.051*	-0.028*	0.048**
	(0.017)	(0.024)	(0.029)	(0.015)	(0.023)
Social Class II	0.002	-0.010	0.018	-0.049***	0.039*
	(0.016)	(0.025)	(0.029)	(0.015)	(0.022)
Social Class III	-0.023	0.010	-0.058**	-0.036**	0.106***
	(0.017)	(0.024)	(0.028)	(0.015)	(0.021)
Social Class IV	-0.039*	0.023	0.074**	-0.085***	0.026
	(0.020)	(0.026)	(0.031)	(0.023)	(0.026)
Social Class V	0.001	-0.027	0.070**	-0.035**	-0.009
	(0.016)	(0.025)	(0.028)	(0.015)	(0.022)
Married	-0.013	-0.017	0.035	0.003	-0.008
	(0.018)	(0.022)	(0.024)	(0.014)	(0.018)
Full-time	0.037*	-0.081***	-0.002	-0.083***	0.129***
	(0.020)	(0.024)	(0.027)	(0.015)	(0.019)
Dependent	-0.005	-0.053**	0.136***	0.013	-0.091***
	(0.017)	(0.023)	(0.027)	(0.015)	(0.019)
School: State	0.004	-0.010	0.043*	0.019	-0.056***
	(0.015)	(0.022)	(0.026)	(0.015)	(0.018)
Ethnicity: Black	0.003	0.071**	-0.183***	0.008	0.100***
	(0.025)	(0.034)	(0.044)	(0.022)	(0.028)
Ethnicity: Asian	-0.010	0.099***	-0.175***	0.005	0.081***
	(0.022)	(0.030)	(0.041)	(0.019)	(0.027)
Ethnicity: Other	-0.002	0.025	-0.061	0.007	0.031
	(0.023)	(0.032)	(0.038)	(0.020)	(0.027)
Log Expected Earnings	-0.583***	-1.427***	-0.941***	0.738***	2.214***
	(0.107)	(0.141)	(0.142)	(0.085)	(0.080)
Observations			3,435		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Table E8: Multinomial Logit Model of Students' Subject Choice (Robustness Check, FT Dependent Students, Specification 1)

	Science	Social Science	Arts & Humanities	Engineering & Applied Subjects	Professional Subjects
Male	0.038***	0.023	-0.129***	0.121***	-0.053***
	(0.014)	(0.019)	(0.023)	(0.013)	(0.018)
Age	-0.020***	-0.004	-0.007	0.004	0.027***
	(0.005)	(0.006)	(0.007)	(0.003)	(0.005)
Parents Studied in HE	0.014	-0.008	-0.038	-0.003	0.035*
	(0.017)	(0.022)	(0.025)	(0.013)	(0.020)
Social Class I	-0.044*	-0.003	-0.000	-0.024	0.071**
	(0.025)	(0.032)	(0.038)	(0.017)	(0.031)
Social Class II	-0.016	-0.040	0.010	-0.058***	0.104***
	(0.026)	(0.035)	(0.040)	(0.020)	(0.031)
Social Class III	-0.025	0.021	0.048	-0.068***	0.024
	(0.027)	(0.035)	(0.041)	(0.022)	(0.035)
Social Class IV	-0.061*	-0.010	0.110**	-0.094***	0.055
	(0.035)	(0.041)	(0.047)	(0.030)	(0.039)
Social Class V	0.011	-0.020	0.055	-0.040**	-0.006
	(0.025)	(0.035)	(0.040)	(0.019)	(0.035)
Married	0.021	0.084*	-0.088	0.002	-0.018
	(0.043)	(0.050)	(0.064)	(0.036)	(0.047)
School: State	0.015	0.008	0.046	0.015	-0.084***
	(0.023)	(0.029)	(0.033)	(0.018)	(0.021)
Ethnicity: Black	-0.196*	0.117*	-0.044	0.037	0.086*
	(0.105)	(0.060)	(0.082)	(0.034)	(0.052)
Ethnicity: Asian	-0.017	0.098***	-0.227***	0.021	0.125***
	(0.031)	(0.035)	(0.050)	(0.019)	(0.030)
Ethnicity: Other	0.008	-0.054	0.008	0.013	0.024
	(0.035)	(0.049)	(0.051)	(0.026)	(0.037)
Observations			1,946		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Table E9: Multinomial Logit Model of Students' Subject Choice (Robustness Check, FT Dependent Students, Specification 2)

	Science	Social Science	Arts & Humanity	Engineering & Applied Subjects	Professional Subjects
Male	0.050**	0.059**	0.010	0.062***	-0.182***
	(0.019)	(0.026)	(0.029)	(0.012)	(0.015)
Age	-0.017***	0.003	0.009	-0.001	0.006
	(0.005)	(0.006)	(0.006)	(0.003)	(0.004)
Parents Studied in HE	0.013	-0.009	-0.042*	-0.003	0.041**
	(0.017)	(0.022)	(0.024)	(0.013)	(0.018)
Social Class I	-0.039	0.010	0.020	-0.030*	0.039
	(0.025)	(0.032)	(0.036)	(0.016)	(0.026)
Social Class II	-0.008	-0.018	0.042	-0.069***	0.053**
	(0.026)	(0.034)	(0.038)	(0.020)	(0.027)
Social Class III	-0.025	0.021	0.043	-0.062***	0.023
	(0.027)	(0.034)	(0.038)	(0.021)	(0.029)
Social Class IV	-0.061*	-0.009	0.101**	-0.087***	0.057*
	(0.035)	(0.041)	(0.044)	(0.029)	(0.033)
Social Class V	0.012	-0.024	0.049	-0.036*	-0.000
	(0.025)	(0.034)	(0.037)	(0.019)	(0.029)
Married	0.022	0.085*	-0.079	0.002	-0.029
	(0.043)	(0.050)	(0.061)	(0.035)	(0.041)
School: State	0.012	-0.002	0.024	0.019	-0.053***
	(0.023)	(0.029)	(0.032)	(0.017)	(0.019)
Ethnicity: Black	-0.198*	0.106*	-0.068	0.039	0.120***
	(0.104)	(0.060)	(0.080)	(0.033)	(0.041)
Ethnicity: Asian	-0.012	0.112***	-0.199***	0.011	0.087***
	(0.031)	(0.036)	(0.048)	(0.018)	(0.026)
Ethnicity: Other	0.010	-0.055	-0.001	0.015	0.031
	(0.034)	(0.049)	(0.049)	(0.025)	(0.033)
Log Expected Earnings	-0.267*	-0.678***	-2.006***	0.876***	2.075***
	(0.148)	(0.189)	(0.207)	(0.104)	(0.095)
Observations			1,946		

Notes: Average marginal effects are reported. Standard errors in parentheses. *, **, *** indicate 10%, 5%, and 1% level of significance, respectively.

Conclusion

Rooted in the theory of human capital investment is the assumption that individuals make educational decisions by weighing **returns to education** against **costs associated with schooling**. From different perspectives of the cost-benefit trade-off, the three papers in this thesis have examined young people's educational decision-making in different contexts and different educational stages.

From the perspective of returns to education, Paper 1 underscores the key role that financial literacy plays in shaping junior high school students' **awareness of educational benefits** and **expectation of future earnings**, in the context of rural poverty in developing countries.

The major strength of our research is to apply the concept of financial literacy in both theoretical and empirical analyses, in an attempt to explore the underlying reasons for students' lack of study motivation even when they are informed about educational costs and benefits. Financial literacy is widely documented in the literature on financial decision-making, and our paper is among the first to examine its impact on educational investment. A particular highlight of our theoretical analysis is that, in a model of human capital accumulation, financially illiterate students are subject to a cognitive bias of "ironing" heuristic and tend to linearize the nonlinear human capital formation. Consequently, they are prone to underestimate marginal returns to education and hence are inclined to expect lower future earnings, resulting in suboptimal educational investments. Moving forward with this assumption, and drawing upon a survey among four schools in a poor county in China, we provide empirical evidence that rural students' financial literacy exerts positive and statistically significant impacts on their perception of educational benefits, consistent with what the theoretical model predicts. Importantly, we find that students with poor knowledge of compound interest are likely to perceive lower returns to education, in line with the theoretical assumption that insufficient financial literacy is associated with linearization bias.

There are a few ways in which our work can be extended in the future. First, in the survey, the information on students' earning expectations was collected without conditioning on their schooling intentions and career aspirations. As a result, the effect of financial literacy on expected earnings could be overstated. This data limitation indicates a direction for our future survey design and data collection. Second, we use students' math score from the most recent final exam to control for their cognitive ability, whereas this proxy might be subject to measurement error. In the paper, we argue that this is not considered to be a big concern, given the existing evidence that math test score is highly correlated with test scores of other subjects and plays a prominent role in explaining the impact of cognitive skills. Nonetheless, to better circumvent the potential endogeneity bias, careful consideration is needed for a more reliable measure of cognitive traits. Third, the results in this paper are most applicable to poor areas in developing countries with similar settings as outlined in the model. Whereas the external validity remains unclear in other contexts, including the wealthier regions within the country and developed countries. Therefore, it would be a worthwhile exercise to extrapolate the current study to other populations.

With an emphasis on the HE students' **educational costs** in the UK over the past six decades, Paper 2 investigates the impacts of net college cost and net liquidity on demand for post-compulsory education in England and Wales.

Using aggregate data collected from various sources, this paper exploits the seismic change in UK's HE finance system, and investigates young people's three-stage schooling decisions in a Seemingly Unrelated Regressions model over a period from 1958 to 2018. To take account of the great variation in HE policies over time, a notable feature of our time-series analysis is to allow for structural breaks, not only in testing the stationarity of the time-series variables, but also in estimating the model by exogenously detecting the timing of the breaks. Within such a framework, we illustrate that significant structural shifts in young people's post-compulsory education decisions occurred in line with several important changes in HE policies. Besides, there are gender differences in the structural break points. Based on these break points, our estimation results show that higher college costs do deter HE participation. Moreover, this adverse impact is larger in magnitude on young males than females. In particular, for the post-1998 era, males appear to be more sensitive to the soaring tuition fees and fee loans. Furthermore, although the past years have seen no evident downward trend in HE participation despite a hike in fees, our policy simulations indicate that, if tuition fees were increased by a larger amount, the detrimental effect of college costs on the demand for HE could be exacerbated, which could in turn give rise to some issues in the equity of educational access to HE.

There are several dimensions along which this study can be improved. The sensitivity to model specifications needs to be more carefully examined. And it would be necessary to take account of a more complete list of candidate break so as to better understand the structural changes. Other limitations of this work should also be noted, mainly due to the data being used. First, as with any exercise to gather time-series data from aggregate statistics, there are concerns about data consistency that inevitably arise from either limited data or changing policies (and variable definitions) from time to time. Although a great amount of effort has gone into constructing data and maintaining its consistency, it is still unclear how reliable some of the data series are, such as the data of internal rate of return which is calculated on the basis of several distinct data sources. Moving forward with the data set, we will have to bear this in mind in our future research. Second, the methodology of structural changes is asymptotic in nature, and as such we must acknowledge that with our relatively small sample size this is a clear drawback of our analysis. Also because the observations are limited, and since a minimum period length must be pre-specified in the structural break tests, it is not feasible to detect some potentially important break points that might have occurred in recent years, for instance, the introduction of fee loans in 2006 and the substantial increases in the cap of tuition fees since 2012. As a robustness check, we re-estimate the regressions by explicitly imposing these hypothetical structural break points, and the results are broadly comparable with our main findings. However, most of the effects lose significance, which again could be attributed to the small sample size for the recent time intervals. Therefore, more caution should be exercised in interpreting any results that draw upon the estimates in the last time interval, and further extension of the data set is needed to address these concerns.

While Paper 1 and Paper 2 are more related with **level of schooling**, paying particular attention to investments in post-compulsory education, Paper 3 looks at **type of education**, that is, field-specific college choices. Highlighting the impact of field-specific **expected earnings**, Paper 3 examines the determinants of undergraduate subject choice in England and Wales.

Apart from expected earnings, the paper also focuses on the role of gender and social class, based on 2004/05 Student Income and Expenditure Survey (SIES). First, both the descriptive statistics and the multinomial logit model of students' subject choice indicate significant gender segregation across subjects, with female students more inclined to choose Arts & Humanities but avoid STEM-related fields especially Engineering & Applied Subjects. Interestingly, the gender differences become less severe for the categories of Engineering and Arts & Humanities when we control for expected earnings in the model. Second, gaps in subject choice across social classes are also observed. In particular, children of higher social class seem to prefer Arts & Humanities. Besides, we find that female students of the lowest socio-economic status (SES) group are least inclined to choose Engineering & Applied Subjects as their field of study, compared with their male counterparts of the same social class or females in other higher SES groups. Finally, the effect of expected earnings on major choices appears to be mixed: there are positive impacts on students' opting for fields of higher payoffs, such as Engineering & Applied Subjects and Professional Subjects, whereas the influences are negative for the probability of choosing less lucrative fields, including Science, Social Science, and Arts & Humanities.

Some limitations of the current work set directions for our future research. First, the grouping of subject fields is constrained by some classifications of majors in the SIES data. For instance, Subjects Allied to Medicine are categorized as Professional Subjects, whereas compared with other subjects in the same category, this particular subject is generally associated with a larger female share and lower earning potentials. As such, evidence related with the subject group could be obscured and thus careful interpretation of the results is warranted. Second, the SIES data lacks information on prior academic achievement which could play a vital role in affecting the choices of college major. To tackle this problem, we can seek to link the data set with exogenous data on prior academic performances. Third, the data set does not provide information about students' expected earnings before they chose their field of study. As the expectation of earnings is one of the key control variables in the paper, we refer to exogenous income data to compute the median annual earning of past graduates, by gender and by subject, and use it to approximate the expected earnings of the cohort in study. Although we have provided some evidence to support our assumption that students are informed about past graduates' salaries, we are still uncertain of the extent to which they would make unbiased expectations based on the information. As such, more caution should be exercised in interpreting related results. Further, more careful work would be imperative to better understand students' expectation of earnings and the role it plays in affecting subject choices.

All in all, human capital accumulation essentially builds on the investment of knowledge and skills that are acquired through education, and in turn plays a vital role in boosting an individual's productivity and thus enhancing any society's economic growth. Given that education is an enormously important component of human capital investment, it is necessary to have comprehensive understanding of an individual's educational decisions. This thesis extends previous research on human capital investment by exploring the determinants of schooling decisions, with focuses on educational costs and benefits. Presented in the thesis are three papers that cover different aspects of students' educational decisions and come to a few significant conclusions.

The rising educational costs prove to exert an adverse impact on demand for education and this effect could differ by gender, while one's subjective evaluation of educational costs also involves the consideration about the opportunity costs of foregone earnings. On the other hand, while expectation of monetary returns - in the form of internal rate of return to schooling or field-specific expected earnings - could matter in an individual's decision on either the number of years of schooling or the choice of college major, the influences turn out to vary over time and across subject choices. Apart from the pecuniary consideration, the difference in non-pecuniary factors appears to explain the variation in one's schooling choice. Moreover, risk aversion and debt aversion could also be significant force behind students' educational decisions.

Furthermore, even if an individual is fully informed about the costs and benefits of schooling, the extent to which the perception about these elements is unbiased remains unclear. In fact, the perception of economic returns to education can be biased due to cognitive limitations such as the "ironing" heuristic. One possible remedy for such a misperception is to promote students' financial literacy, which is found to alleviate cognitive bias and thus encourage participation in education, especially for junior high school students in poor rural areas in developing countries.