The Impact of Local Unemployment on 18-Year-Olds Entering into UK Universities: A UK Panel Data Analysis

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Abstract

This dissertation examines the link between local working-age unemployment rates and the entry rate of 18-year-olds to UK universities from 2006 to 2021. Analysis uses a panel of 120 NUTS3 areas (geographical divisions of UK economic area) and a least squares approach employing time and entity fixed effects. Analysis controls for variables such as gross disposable household income (GDHI), GDP per working-age individual, university wage premium, and the percentage of the population with at least a university-level education. Due to the differing educational structures and economic compositions present throughout the UK, separate regressions were undertaken to explore the geographical and socio-economic angles of enrolment decisions. The initial hypothesis posited a positive, statistically significant impact of local unemployment on 18-year-olds entering university education. Initial regressions covering 120 UK NUTS3 areas, England and Wales, and Scotland did not support this hypothesis. Dividing the 103 English and Welsh NUTS3 levels into lower- and higher-income panels revealed a small, significant negative effect of unemployment on university entry in lower-income areas (5% significance level), with no significant effect in higherincome areas. Quantifying this, a 1% increase in local unemployment decreases the university entry rate of 18-year-olds from lower-income areas by 0.7%. GDHI emerged as the most influential factor, positively affecting university entry in lower-income areas of England and Wales, but not in Scotland or higher-income areas. Results from this research contribute to a currently lacking evidence base exploring the drivers of university enrolment decisions; Interpreting this analysis in a policy context, policymakers targeting improvements to the UK education level should remain cognisant of the discovered negative effect of local unemployment in lower-income areas of England and Wales, responding effectively with targeted policy. Reassuringly, the strong significance of GDHI for these areas indicates policy addressing financial constraints is likely to be effective, albeit small in magnitude.

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1. Introduction

As defined by the OECD, 'human capital' is "the stock of knowledge, skills and other personal characteristics embodied in people that helps them to be productive" (OECD, 2022). Over their lifetime, individuals face multiple decision points where they either opt to 'invest' in their human capital by continuing in formal education or pursue alternative options like joining the labour force. Explored specifically throughout this dissertation is the decision at age 18, where UK individuals decide whether to undertake undergraduate-level university education.

Through obtaining undergraduate-level education, on average individuals attain higher average lifetime earnings (even after considering taxes, student loans, and the opportunity cost of education) and an improved likelihood of employment (DBIS, 2013). The ONS (2023) calculate the yearly real-terms salary premium for graduates over non-graduates is circa (c.) £8,000, with graduate working-age employment at 87.3% (69.6% for non-graduates). Education also has wider positive spillovers for society. Educated citizens foster innovative ideas, stimulating economic growth and subsequently, paying higher taxes and costing governments less in terms of social entitlements/welfare. This is particularly acute at the tertiary (university) level (OECD, 2023).

Despite university education seeming advantageous, not all 18-year-olds pursue university education. Traditional literature first exploring the key determinants of these post-compulsory education decisions focused extensively on the wage premium and improved job prospects highlighted prior (Becker, 1962; Ben-Porath, 1967). Ensuing literature built upon this framework by highlighting broader factors, such as the importance of inherent ability and academic achievement of individuals (Micklewright, et al., 1990), the income of prospective students and their families (Rice, 1999), education culture (Desforges & Abouchaar, 2003), cyclicality of

decisions (Barbu, 2015), and, most importantly for this analysis, the impact of local labour markets (Nickell, 1979; Freeman, 1986; Clark, 2011).

UK literature thus far has been unable to reach uniform conclusions. Alongside this obvious limitation, research is outdated and focused primarily on further education rather than university education.

1.1.Purpose of this dissertation

This paper will expand upon research into the determinants of human capital investment decisions by providing a modern assessment of the relationship between local unemployment and university entry. To fulfil this purpose and explore variation across the UK, five regression analyses are completed: (1) The whole UK, (2) England and Wales, (3) Scotland only, (4) Low-income areas, and (5) High-income areas. Understanding the exact role of local labour market conditions in university entry decisions will enable policymakers to implement more effective higher-education policy.

1.2.Disposition

This dissertation is structured as follows: *Section 2* provides the background necessary for interpretation. *Section 3* outlines the theoretical framework and relation to the literature. *Section 4* presents the empirical framework (including variable selection and methodology). *Section 5* reports the findings from conducted regression analyses. *Section 6* outlines potential limitations in approach. Finally, *Section 7* summarises the project outcomes and policy recommendations.

2. Background

2.1.Cost of university throughout the UK

In 1998, responsibility for higher education was devolved to Northern Ireland and Scotland, with this later extended to Wales in 2006 (Atherton, et al., 2023). Consequently, university education systems across the UK differ considerably. Most relevant for this study are the differences in financing, dependent on the student's home region and location of study (*Table 1*).

 Table 1: Maximum 2023 to 2024 tuition fees by country (UCAS, 2024)

Student's domicile	Studying in England	Studying in Scotland	Studying in Wales	Studying in Northern Ireland
England	£9,250	£9,250	£9,000	£9,250
Scotland	£9,250	No fee	£9,000	£9,250
Wales	£9,250	£9,250	£9,000	£9,250
Northern Ireland	£9,250	£9,250	£9,000	£4,710

Whilst tuition fees for English and Welsh students are comparable, Scottish and Northern Irish students opting to study at domestic universities have consistently paid no fee and a reduced fee respectively post-devolution. Given marked differences, contrasting drivers of education enrolment across the UK are to be expected. UK students do however receive comparable student finance generosity, "usually consisting of a Tuition Fee Loan and a Maintenance Loan to cover – or at least partially help with" university costs (UCAS, 2024).

2.2. Recent trends in UK university enrolment and unemployment

The UK has a strong culture of university enrolment, with 26% of all 25-64-year-olds possessing an undergraduate-level degree – 7pp higher than the 19% OECD average (OECD, 2022). As seen in *Figure 1*, one key contributory factor is the recent upward trend of 18-year-olds enrolling into UK universities (UCAS, 2024).



Exploring enrolment trends geographically, the university entry rate (% of the 18-year-old population) is generally higher in wealthier, more densely populated domiciles in the South of the UK. In 2022, West and Northwest London presented with the highest entry rate at c.57%, but all London domiciles (where employment often requires advanced skills) demonstrated an entry rate exceeding 47%. Angus and Dundee city possessed the lowest entry rate (c.23%), despite Scottish universities not charging fees to students from Scottish domiciles. West Cumbria had the lowest entry rate in England and Wales (c.24%). Occupations most in demand for this region are "kitchen & catering assistants, care workers, cleaners & domestics, nurses and sales

occupations" (Cumbria Intelligence Observatory, 2023), where university education is often not a requirement. This highlights the role of labour market complexion in enrolment decisions. Various factors influence the level of unemployment, however increases are commonly associated with economic crises. UK working-age (16-64) unemployment fluctuates, but two main increases are witnessed during the 2006-2021 period. Stimulated by the Global Financial Crisis (GFC) the national unemployment rate rose from 5.7% in 2007 to 8.3% in 2011 (ONS, 2024), also increasing during the 2020 COVID-19 pandemic (albeit less profoundly (+0.8pp) given the mitigating role of various employment support schemes enacted by the UK government (National Audit Office, 2020)). Notable variation in the unemployment rate is also witnessed throughout the UK, linked to the region's economic prosperity: Birmingham averaged c.10.4% over the period studied, however, Oxfordshire averaged 3.4% throughout.

Initial correlation tests between the two variables at a national level result in a figure of -0.63, indicating a moderate negative relationship. Correlation tests can, however, be misleading as correlation does not always imply causation, and so ensuing regression analysis is vital to robustly assess the potential causal effect.

3. Theoretical framework and relation to the literature



3.1. Human capital theory and empirical framework

Gary Becker (1962) was one of the first economists who recognised education decisions as investments. Plotting a downward-sloping marginal rate of return ('demand') curve and an upward-sloping marginal cost ('supply') curve in a static context (*Figure 2*), Becker suggests additional education is undertaken if the expected benefits exceed the costs (Becker & Chiswick, 1966). Becker focused initially on wage increases associated with improved education; downward-sloping due to the diminishing marginal product associated with adding more capital (education) to a human body. Marginal costs were mainly the direct monetary costs (e.g. school/university fees), upward-sloping to reflect the hierarchy of education financing (borrowing first from parents and later, large institutions charging increased 'interest').

Ben-Porath (1967) treated Becker's work (1966) dynamically, exploring the accumulation of human capital over a lifetime. In addition to monetary costs, Ben-Porath majored on the opportunity costs of education, equivalent to foregone earnings at the current education level.

Subsequent research further built upon this pioneering work, detailing wider determinants of enrolment decisions. Nickell (1979), and later Freeman (1986) were the first to allude to the demand-side impact of labour market conditions. Card and Lemieux (2001) later internalise the demand-side effect of individual preferences between school versus work, also improving the supply-side drivers by acknowledging education supply constraints.

As outlined by Clark (2011), then tailored to improve relevance to this study, research culminated in the following econometric model of education enrolment:

$$P(E_{inlt} = 1) = P(\beta_0 + \beta_1 U_{nlt} + \beta_2 X_{inlt} + \beta_3 Z_{nlt} + \beta_4 W_t > 0),$$

where E_{inlt} denotes whether or not individual *i* in NUTS3-level *nl* in year *t* enrols, U_{nlt} denotes the NUTS3-level unemployment, and the set of relevant control variables have been portioned into those varying at the individual level (included as X), those varying at the NUTS3-level (Z), and those varying at the national level (W) (Clark, 2011, p. 525).

3.2. Unemployment impacts

When exploring the relationship between unemployment and the continuation of education, it is found to be multifaceted, with the effect of unemployment on individuals' demand for continued education deemed ambiguous (Kodde, 1988; Taylor & Rampino, 2014; Meschi, et al., 2018).

Theoretically, as high unemployment reduces the likelihood of obtaining work, the opportunity cost of education is lower. This factor, combined with the expected gain from job search, induces the so-called "*discouraged worker effect*", whereby young people continue in education due to reduced motivation to enter the labour market (Meschi, et al., 2018). Relatedly, in instances where increased unemployment is concentrated among lower-skilled jobs (primarily undertaken by those with fewer qualifications), incentives to remain in education are stronger in order to

succeed in more difficult labour market conditions – defined as the "insurance effect" (Tumino & Taylor, 2015).

Despite this, the above relationship assumes the presence of perfect information at the time of decision. In reality, education decisions are often guided by inaccurate perceptions of the returns to education (Jensen, 2010), both those of prospective students and their parents, who are known to play an important role in educational decisions (Christoph, et al., 2024). A weak labour market *may* be interpreted as an indication that obtaining work in the future will be more difficult, hence reducing the return to education via the "*discouraged student effect*" (Micklewright, et al., 1990) as students view it as a necessity to secure a job promptly.

In addition to this, perceptions of the local labour market may also be inaccurate. Despite local unemployment estimates being published, they are often not readily known, with prospective students instead guided by first-hand experience (e.g. from applying to jobs and/or the experience of their friends and family). This is often subject to under/overestimation. Contrarily, as highlighted by Barbu (2015), national-level indicators receive notable media coverage and resultantly, are more widely known by individuals. Should prospective students be guided by either inaccurate interpretations of the local economic climate or national-level unemployment data (known to diverge from the local-level measures), the <u>actual</u> measured local unemployment rate may be insignificant in decisions.

3.3. Existing empirical literature

Thus far, literature has been unable to reach a uniform view on the direction or magnitude of the relationship between unemployment and post-compulsory education. UK-specific research focuses extensively on both further education (ages 16-18) and national-level indicators, with

few instances concerning higher education or local unemployment. Subsequently, wider geographical research is also included. Papers utilise both micro- and macro-based econometric techniques, summarising short-run and long-run trends, and differentiating by individual characteristics (e.g. gender, ethnicity, etc.).

3.3.1. UK macro-based time series analysis

Pissarides (1982) was one of the first to explore the key drivers of enrolment in UK postcompulsory education. Exploring between 1955-1978, Pissarides concluded that unemployment was insignificant and "does not seem to exert a significant influence on education decisions beyond the age of 16." (Pissarides, 1982, p. 662). Instead, key drivers of enrolment were real household income and the wage premium. Extending this analysis to cover 1955-1985, Whitfield and Wilson (1991) claim a positive, albeit small, statistically significant relationship for further education. Noting a general decrease in the explanatory power of Pissarides' model (1982) they formulate a new model based on a vector auto-regressive (VAR) model: the unemployment elasticity then increases further to 0.1 (at 1985 sample means). Utilising the VAR framework and updating the series further (1955-94), Mcvicar and Rice (2001) find comparable results. Using a cointegration framework between 1961-1994, Mcintosh (2001) widens research to cover

higher education. Similarly, Mcintosh concludes that unemployment has a small, positive, significant effect on further education enrolment, but no significance for higher education enrolment.

3.3.2. UK micro-based analysis

Micklewright *et al.* (1990) utilised family expenditure survey (FES) data to first experiment with a micro-based, binary logistic regression study. Through this approach, they were unable to conclude that any of the increased further education enrolment between 1978-84 stemmed from

rising unemployment rates. Exam performance and higher education supply were instead found to be most significant in influencing enrolment decisions. Results were sensitive to specification. Building upon this research using three separate waves of the Youth Cohort Study (YCS) survey (1988/1990/1991), Rice (1999) finds that county unemployment has relatively strong effects, however, due to the short length of the panel and omission of county fixed effects, these results are deemed imprecise.

Later, covering the period 1994-2010, Taylor and Rampino (2014) conclude that during periods of high unemployment, children are less likely to report as wanting to leave school at 16 (intensifying for those with parents who view A-levels as important). Conflictingly, between 1991-2008, Tumino and Taylor (2015) find unemployment only increases enrolment for individuals in rented housing (otherwise insignificant). Findings by Meschi *et al.* (2018) conclude the local youth labour market is insignificant in influencing the decision to continue with or leave education.

3.3.3. UK macro-based panel data analysis

Damon Clark (2011) utilises a panel of 9 English regions (excl. Scotland due to differences in the enrolment environments and Wales due to data constraints) over 1975-2005. Assessing the impact of local youth unemployment specifically on further education Clark finds strong, positive effects.

3.3.4. Wider geographical higher education analysis

The direction and magnitude of unemployment effects in broader geographical research are largely dependent on the country(ies) and period studied. Whilst not directly comparable to the UK, they provide useful context.

United States

Using a panel of US states spanning 1960-1990, Card and Lemieux (2001) find that unemployment effects are weak and variable in sign depending on specification, with some indication of a negative effect. Barr and Turner (2013) construct a separate US state panel, this time covering 1978-2011, finding significant, positive effects of unemployment on enrolment between 2004-2011, with the relationship turning negative and insignificant when looking across the whole 1978-2011 period. Barbu (2015), using a further US state panel (1987-2010), found increases in State-level unemployment have a significant, negative effect on total enrolment. Micro-based research by Dellas and Sakellaris (2003) explored effects over 1968-1988, finding the probability of enrolment increased very slightly when unemployment increased. Long (2014) uses a novel difference-in-differences approach to assess the impact of the GFC – 2007Q1 the control, 2009Q4 the treatment – finding post-recession unemployment growth was slightly correlated (10% significance level) with increased enrolment, becoming negative and insignificant when unemployment growth exceeded 6.5%.

Europe

Most European literature hails from countries where university tuition is inexpensive relative to England and Wales (comparable to Scotland). Despite providing an alternative perspective, conclusions again differ. Kodde (1988) explores Dutch higher education provision during the 1980s finding that increased enrolment is partially driven by youth aspiring to achieve enhanced employment prospects. Fernández and Shioji (2000) use a panel of 15 Spanish regions between 1983-1992 and find differing unemployment effects in the short run, with negative effects present in the long run. Nero and Nordberg (2023) find significant, positive unemployment effects using a panel of 289 Swedish municipalities covering 2000-2021.

Wider analysis

Finally, an Australian simultaneous equation model using 2013 survey data found that unemployment causes a significant reduction in the probability of staying in school (Alam & Mamun, 2016). Additionally, a micro-based study of OECD survey data (covering 1981-2011) found varying effects dependent on the European-country grouping studied, with unemployment insignificant for the grouping encompassing the UK (Graves & Kuehn, 2021).

3.4. Hypothesis for this study

With a thorough review of the empirical evidence providing both supporting and contradictory conclusions, the hypothesis for this study will be guided by core economic theory (assuming perfect information): rising unemployment will act to increase entry into university for all geographical regions and income levels studied. However, conclusions will be drawn knowing positive, negative and zero effects are common throughout the literature.

4. Empirical framework

4.1. Data

This project draws primarily from publicly accessible secondary data sources, published online or sourced via direct enquiries¹. Through these avenues, a balanced panel dataset was compiled, consisting of yearly data spanning 2006 to 2021, and consisting of 120 UK NUTS3-level domiciles². NUTS3 is the most detailed level of the European Union's 'Nomenclature of Territorial Units for Statistics (NUTS)', a hierarchical system that divides up UK economic territory (European Parliament, 2023). Although further disaggregation and a full transition to 'International Territorial Levels (ITLs)' terminology has occurred post-2006, this analysis manually re-aggregates to the 2006 NUTS3 classification to ensure consistent geographical subdivisions throughout.

This period will provide a modern assessment of the relationship between unemployment and university entry rate but was ultimately guided by the inability to source UCAS data pre-2006. The selection of panel data, as opposed to cross-sectional or time-series, was a deliberate decision to enable more accurate inference of model parameters and greater capacity to capture the complexity of human behaviour (Hsiao, 2006).

4.2. Variables and construction of variables

The **dependent variable** used throughout this analysis is the 18-year-old entry rate into UK university education for each NUTS3 domicile. Sourced from UCAS (2024), entry rate is defined as the proportion of the 18-year-old population who are accepted into UK universities

¹ Data will be shared upon request.

² Northern Ireland, island groupings, two Scottish and two Welsh levels, and Blackpool were excluded as a consequence of incomplete data.

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and have been "placed for entry into higher education" (UCAS, 2024). Similar to Card and Lemieux (2000) and Mcintosh (2001), rates are used to standardise by population, controlling for yearly cohort supply constraints and population differences. Therefore, a population variable is not required.

UCAS data on entry rate is preferred over HESA data detailing actual enrolments (HESA, 2024) as they are largely comparable, with UCAS publicly available at a more disaggregated level, enabling greater statistical power and improved model inference.

Included as the **independent variable** is the working-age unemployment rate for each NUTS3 level, manually constructed by dividing the number of unemployed working-age individuals by the number of economically active working-age individuals for each NUTS3 level. Data is sourced from the ONS Annual Population Survey (APS) and was accessed via the Nomis website (Nomis, 2024).

To avoid endogeneity issues and improve estimation, it is important to build a more comprehensive picture: included within this study are further **control variables** outlined by scholars as having influence.

Firstly, almost all literature to date includes a measure of income (Pissarides, 1982; Whitfield & Wilson, 1991; McVicar & Rice, 2001; Clark, 2011; Tumino & Taylor, 2015). This analysis selects Gross Disposable Household Income (termed GDHI), sourced from the ONS (2023), and used to represent economic diversity and social welfare for each NUTS3 level. By representing the actual capital available (after adjustments for tax, rent or mortgages), GDHI effectively proxies the capacity of prospective students (or more likely their families) to finance education. GDHI is expected to have positive enrolment effects in England and Wales but play a less

significant role in Scottish enrolment decisions (in line with Swedish studies where university education is free of charge (Nero & Nordberg, 2023)).

Previous research has explored the effects of university Wage Premium (WP) on enrolment decisions (Freeman & Katz, 1976; Topel, 1997; Card & Lemieux, 2001; Clark, 2011). Calculating WP, the average hourly wage for individuals possessing a higher education qualification was divided by the equivalent figure for those who only completed upper secondary education. This data is publicly available but is not published so was sourced via direct enquiry to ONS (data available upon request). Labour Force Survey data is used between 2006-2011 before transitioning to the APS for the period 2012-2022.

The third control variable is the Gross Domestic Product (GDP) per working-age individual (termed GDPWA). Local-level GDP was sourced from the ONS (2023) before standardising by dividing by the number of working-age individuals. Previous research looking specifically at the United States found that Gross State Product (GSP) has a strongly significant effect on enrolment decisions and, combined with unemployment measures, helps to bring out the potential cyclicality of enrolment decisions (Dellas & Sakellaris, 2003; Barbu, 2015). Despite the geographical disaggregation of UK NUTS3 being notably smaller than the US states used in comparable analysis, this variable is still deemed likely to have significant effects.

The final control variable is the share of the working-age population with undergraduate-level education (termed DS), sourced from the ONS APS (Nomis, 2024) to proxy the local culture of higher education enrolment. Burgess et al. (2018) show that successful UK university-level applications significantly increase in scenarios where prospective students can 'role model' the experiences of university students hailing from similar backgrounds as them, with parental

education level also shown to be an important predictor of children's educational outcomes

(Davis-Kean, 2005).

Variable	Description	Expected sign	Summary statistics	Source
ER	Share of 18-year-old		Maximum: 57.7%	UCAS
	population placed		Minimum: 11.6%	(2024)
	for university entry	N/A	Mean: 28.5%	
	5 5		St Dev: 6.5%	
			Observations: 1920	
U	Local		Maximum: 16.0%	ONS
	unemployment rate		Minimum: 0.9%	(2024)
	1 2	+	Mean: 5.9%	
			St Dev: 2.4%	
			Observations: 1920	
GDHI	Average gross		Maximum: £57,997	ONS
	disposable		Minimum: £10,065	(2023)
	household income	+	Mean: £16,941	
			St Dev: £4,152	
			Observations: 1920	
WP	University Wage		Maximum: 5.7	ONS
	Premium		Minimum: 0.4^3	(Data
		+	Mean: 1.6	request)
			St Dev: 0.30	
			Observations: 1920	
GDPWA	GDP per working-		Maximum: £286,086	ONS
	age individual		Minimum: £10,028	(2023)
			Mean: £40,664	
			St Dev: £22,206	
			Observations: 1920	
DS	Share of working-		Maximum: 85.2%	ONS
	age population with		Minimum: 11.1%	(2024)
	undergraduate-level	+	Mean: 31.0%	
	education		St Dev: 10.8%	
			Observations: 1920	

 Table 2: Summary of variables (covering 120 NUTS3 levels, 2006-2021)
 Particular

³ Although the trend is generally upward, sampling variation gives rise to values <1. Omitting regions with small samples did not change WP significance.

4.3. Selection of specification

Prior to any regression analysis, data was first inspected to assess whether any data transformation was necessary to improve model fit and accuracy of results.

Despite unit roots being unlikely to cause serious errors in panel data estimation (Kao, 1999; Baltagi & Kao, 2000) data is tested for a unit root using the Levin-Lin-Chu (L-L-C) test (Levin, et al., 2002). For all variables, the presence of a unit root was able to be rejected: non-stationarity is not present; unreliable and spurious results are improbable.

Histograms of each of the variables in level form were then created to assess data normality and potential transformations required to improve model fit. Entry rate demonstrated a normal distribution and so was retained in level form, whilst all explanatory variables displayed presented with skewness and so were analysed in their natural logarithmic form. This resulted in a level-log specification.

Most prospective students apply to university through the main scheme process, where applications must be submitted by the January deadline (UCAS, 2024). As application drafting is a substantial time commitment, enrolment decisions largely take place in the year before university entry (to enable students to meet the deadline). Subsequently, given the economic conditions present during the year prior will likely be more informative in decision-making, explanatory variables are lagged by one year for all regression analyses (denoted *t-1* throughout). Following initial data testing, the model selection process commenced. As summarised previously, a thorough review of the literature suggests the following micro-level econometric model of entry into post-compulsory education (see section 3.1 for further context):

(1)
$$P(E_{inlt} = 1) = P(\beta_0 + \beta_1 U_{nlt} + \beta_2 X_{inlt} + \beta_3 Z_{nlt} + \beta_4 W_t > 0)$$

Since this analysis uses panel data techniques, specific individual-level variables (e.g. enrolment decisions and household disposable income) are aggregated to the NUTS3-level, with the resulting specification as follows:

(2)
$$\overline{ER_{nlt}} = \beta_0 + \beta_1 l_{-} U_{nlt-1} + \beta_2 l_{-} \overline{X_{nlt-1}} + \beta_3 l_{-} Z_{nlt-1} + v_{nlt}$$

where the upper bars denote NUTS3 level averages, and l_{-} and t-l represent the aforementioned natural logarithmic transformations and lags. An initial pooled-Ordinary Least Squares (OLS) regression was then conducted, finding a significant negative coefficient for the local unemployment rate. Whilst outputs from this model give an indication of any potential relationship, alongside other limitations, Pooled OLS models do not distinguish between any unobserved entity-specific factors and are unable to control for any changes present at the national level. Subsequently, omitted variable bias is likely and results are often inaccurate (Baltagi & Griffin, 1984).

More comprehensive panel data analysis in this area (Fernández & Shioji, 2000; Card & Lemieux, 2001; Clark, 2011; Barr & Turner, 2013; Nero & Nordberg, 2023) improve this specification by introducing entity (NL) and time (T) fixed effects. As outlined by Clark (2011), employing a two-way Fixed Effects model specification intends to capture the omitted national level variables (W) like changes to the compulsory age of education, as well as controlling for any unobservable heterogeneity (e.g. any omitted individual- and NUTS3-level controls (X and Z) outlined in equation (1)). This results in the near-final model specification:

(3)
$$\overline{ER_{nlt}} = \beta_0 + \beta_1 l_0 U_{nlt-1} + \beta_2 l_0 \overline{X_{nlt-1}} + \beta_3 l_0 Z_{nlt-1} + NL + T + v_{nlt}$$

Testing the adequacy of Fixed Effects for this specific analysis, an F-test was run to assess whether the inclusion of entity fixed effects was preferable to the basic Pooled OLS

specification. The resulting p-value was significantly smaller than 0.05 (~0) and thus, the null hypothesis that pooled OLS is preferable was rejected: modelling proceeds with entity fixed effects. Testing the relative importance of time fixed effects, a second F-test was employed – the null hypothesis that time fixed effects have no significance and all variables are time-invariant was rejected: the resulting output was a P-value<0.05 (3.751e⁻⁰⁴⁸). Time fixed effects are extremely significant, and the two-way time and entity Fixed Effects model (*3*) is most applicable.

Whilst there are benefits to using Random Effects models (e.g. accounting for unobserved heterogeneity), given panel data used in this analysis is of UK NUTS3 levels, there are no random samples in this data. Moreover, NUTS3 levels often demonstrate notable variations in size and/or population density, and so would not be homogenous. Therefore, it is unlikely a Random Effects model would be suitable, with a fixed intercept for each NUTS3 level (as opposed to a common intercept that represents the mean) likely more applicable. To confirm this line of thought, a Random Effects model was tested and compared to Fixed Effects specification by conducting a Hausman test. The null hypothesis is that the Random Effects model is preferred. With the resulting P-value<0.05 (2.743e⁻⁰¹²), the null hypothesis is rejected and, in line with the above thinking, Fixed Effects is preferable.

Continuing with a Fixed Effects approach, concerns are present that unemployment might (because of reverse causation) be endogenous to enrolment in university education and therefore, may bias estimates of coefficients due to the negative effect of continued education on unemployment. Damon Clark's (2011) focus on <u>youth</u> unemployment meant endogeneity was a more acute concern, however, through widening the scope of unemployment to capture the whole 16-64 population, endogeneity is expected to have less of a profound influence: the 18-

year-old age group represents a minimal segment of the total 16-64 population. Hence, enrolment decisions are not expected to significantly alter local unemployment rates. Despite this, alternative specifications were tested but ultimately, an effective alternative was unable to be sourced. Key literature utilises a lagged value of unemployment as the primary instrument in a Two-stage Least Squares (2SLS) regression. When testing this approach via the Sargan overidentification test (1958), where the null hypothesis is that the model was correctly specified, this was rejected (1.148e-005<0.05) and this instrument was found to be invalid. In line with Clark (2011), estimation remains through least squares, noting any endogeneity will bias estimates and lead to a misinterpretation of unemployment effects, although this is expected to be marginal.

Finally, proceeding with the two-way fixed effects specification, the Breusch Pagan test (1979) for heteroscedasticity (null hypothesis is that heteroscedasticity is not present), and the Durbin-Watson test (1951) for serial correlation (null hypothesis is that serial correlation is not present), were employed to assess the current robustness of results. For each test, the associated P-value was found to be <0.05 meaning both are currently present. As heteroscedasticity violates the OLS classical assumption of the error term having a constant variance, with serial correlation also violating the classical assumption of zero correlation between the errors, current model results are invalid. To mitigate the effects of the above, given the panel is of the "large n, small T" variety (Arellano, 2003), Arellano robust standard errors were applied, clustered by cross-sectional unit to account for the likely cross-sectional dependence discovered through the Pesaran CD test (2015).

4.4. Final model specification

All separate analyses followed the specification selection process summarised previously, with the below specification deemed to provide robust, unbiased results throughout. The selected final

model was a Fixed Effects specification over the period 2006-2021, including time (T_t) and NUTS3-level/entity (NL_i) fixed effects. All models implement Arellano robust standard errors:

$$ER_{nlt} = \beta_0 + \beta_1 l_U_{rt-1} + \beta_2 l_G H D I_{nlt-1} + \beta_3 l_W P_{nlt-1} + \beta_4 l_G D P W A_{nlt-1} + \beta_4 l_D S_{nlt-1} + \lambda N L_i + \gamma T_t + v_{nlt}$$

The dependent variable of NUTS3 level entry rate to university education (ER_{nlt}) is presented in level form at time t, with the endogenous independent variable of NUTS3 level unemployment rate (l_Ur_{t-1}) and all control variables (Gross Disposable Household Income, Wage Premium, GDP per working-age individual, and Degree Share) analysed in their natural logarithmic form at time *t*-1. λNL_i = entity fixed effect, γT_t = time fixed effect, v_{nlt} = the error term.

5. Results and discussion

Given the differences in educational structures present throughout the UK, *Table 3* presents the results from three separate regression analyses, differentiating by UK geographical area.

5.1.Geographical analysis

Table 3: Core geographical analysis: Results of fixed effects regression on ER, 2006-2021.

Variable	Whole UK enrolment	England and Wales enrolment	Scotland only enrolment
<i>l_U</i>	-0.003	-0.003	0.001
	(0.002)	(0.003)	(0.006)
l_GDHI	0.194***	0.193***	-0.046
	(0.053)	(0.058)	(0.073)
l_GDPWA	-0.067**	-0.065*	0.161
	(0.033)	(0.035)	(0.044)
l_WP	0.005	0.004	0.006
	(0.003)	(0.003)	(0.006)
l_DS	-0.006	-0.007	-0.001
	(0.010)	(0.011)	(0.014)
const.	-1.783**	-1.766***	0.579
	(0.553)	(0.595)	(0.742)
Obs.	1800	1545	255
No. of NUTS3 levels	120	103	17
R-squared (within)	0.809	0.831	0.758

Notes: Significance levels indicated as ***<0.01, **< 0.05, *<0.1. Robust standard errors are in parentheses.

Given the specification's level-log form, to adequately quantify impacts, the semi-elasticities above are transformed using the approach set out by Rutledge (2018), remaining cognisant that the dependent variable is a share of the total population (1 unit change = 100% increase), with control variables also presenting in differing forms (%/£).

Discussion throughout the following section assumes ceteris paribus: when discussing the causal effects of individual explanatory variables, all other variables of inclusion are held constant to isolate effects, maximising the usefulness in informing policy.

Guided by *Table 3*, this study finds that local unemployment does not have a significant effect on entry to university in any of the geographical subdivisions studied, failing to provide evidence supporting the paper's hypothesis that unemployment would have a significant positive effect on entry into university education. These conclusions are thus far, in line with that of Mcintosh (2001), where unemployment was not found to have significant effects on higher education decisions.

Moving to discuss the wider variables included, perhaps one of the most interesting inferences is the role of GDHI in influencing university entry. In line with Pissarides (1982), GDHI (income) is seen to have a positive, statistically significant effect (1% level) on university entry in the UK. This relationship looks to be solely driven by England and Wales, turning negative and insignificant when exploring the relationship in Scotland specifically. Using the methodology outlined above, a 1% increase in average GDHI would result in a 0.194% increase in the university entry rate in England and Wales.

Student finance commonly covers course fees in addition to a maintenance loan to help towards living costs. Support is more generous for prospective students enrolling from households at the lower end of the income distribution, reflecting the relative capability of their family to contribute towards living expenses (GOV.UK, 2024). Interpreting these results, whilst we find student finance likely reduces the magnitude of the impact income differentials have on university entry, it does not eliminate it. Increases in GDHI mean parents are more able to cover the differential between living costs and the maintenance loan received and hence, barriers to Kent Economics Degree Apprentice Research Journal, Issue 2, 2024. university education decrease as income increases. Whilst less likely due to student loans not requiring repayment until earnings exceed a minimum £24,990 threshold (GOV.UK, 2024), results could also reflect the willingness to take on debt (i.e. student loans) – students from poorer households may be more reluctant due to the more generous loans received. It is also interesting to note that GDHI is insignificant when exploring the relationship for Scotland. As domestic students at Scottish universities are not required to pay university fees, any role of income differentials is potentially eliminated.

Another interesting outcome, in line with Dellas and Sakellaris (2003) is the negative, statistically significant (5% level) relationship between GDPWA and entry to university education. Whilst effects become smaller and less significant (10% level) for England and Wales specifically, this indicates that during the business cycle, there is "a significant substitution between human capital investment and competing activities" (Dellas & Sakellaris, 2003, p. 163). As unemployment and GDP often move in unison, potentially introducing multicollinearity into this analysis, regressions were re-conducted with the GDPWA variable omitted. This did not affect results (see *Section 6*).

When assessing the accuracy of model fit, this is at its highest point when modelling England and Wales only, with approximately 83% of the relationship explained by the variables included in this regression model. Despite not being included in *Table 3* for brevity, it is important to note the strong significance of both entity and time fixed effects, suggesting that both national and entity-specific factors have a strong influence over enrolment decisions. Whilst it is favourable that these factors are captured, this represents a limitation to this analysis (see *Section 6*).

Neither the wage premium nor the degree share variables were significant in any of the above specifications, with the latter often having a sign contrary to what the literature would expect.

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However, as these variables were shown to improve model fit and have a strong presence in the literature, they were retained throughout. These findings are in line with Clark (2011) who utilises a similar UK panel approach. A possible explanation for this phenomenon (that could be extended to the insignificant unemployment variables in the geographical analysis), is one outlined by Oreopoulos (2006): the national-level measures of these variables (controlled for in this analysis by strongly significant time fixed effects) is likely to have a more significant effect on entry decisions. Possible next steps to internalise these factors were identified for future research and have been outlined in *Section 6*.

5.2. Socio-economic analysis

Introducing a further angle to this analysis, the 103 NUTS3 levels for England and Wales were divided into two panel datasets. The first covers the 51 NUTS3 levels that presented with the lowest average GDHI over the 2006-2021 period (to proxy lower socio-economic regions), and the second, the 51 possessing the highest average GDHI (to proxy higher socio-economic regions). Using the section 4.3 specification, *Table 4* outlines results.

Variables	Low-GDHI areas enrolment	High-GDHI areas enrolment	
Ln_UNEMP	-0.007** (0.003)	-0.004 (0.004)	
Ln_GDHI	0.205*** (0.075)	0.079 (0.058)	
Ln_GDPWA	-0.090** (0.041)	-0.050 (0.050)	
Ln_WP	0.002 (0.005)	0.002 (0.003)	
Ln_DEGSHARE	0.007 (0.012)	-0.017 (0.017)	
const.	-1.972*** (0.736)	-0.591 (0.602)	
Obs.	765	765	
No. of NUTS3 regions	51	51	
R-square (within)	0.805	0.866	
Notes: Significance levels are indicated as ***<0.01, **< 0.05, *<0.1. Robust standard errors in parentheses.			

Table 4: Core geographical analysis: Results of fixed effects regression on ER, 2006-2021

Exploring the relationship at different income deciles, the key variable of interest (local unemployment) is shown to be a determining factor for the lower-income panel (significant at 5%) but not for the comparable higher-income panel. One potential explanation for this polarity is the effect of labour mobility. As outlined by the Social Mobility Commission (2020), regional outward migration is significantly less likely when individuals hail from lower socio-economic backgrounds (relative to higher socio-economic), with this particularly acute for those exhibiting lower qualification levels. Resultantly, prospective students from poorer areas are more likely to factor local labour market conditions into enrolment decisions, whereas higher-income regions could be more influenced by national unemployment indicators. Whilst all included variables are insignificant in the high-income regression, the strong model fit is driven by strongly significant time fixed effects, evidencing the potential importance of national-level indicators relative to the local level.

Looking specifically at the direction of the local unemployment relationship, the results of the first regression directly contradict the initial hypothesis, instead finding a negative relationship present. Quantifying this, we find relatively small effects, with a 1% increase in the local unemployment rate associated with a 0.7% reduction in the university entry rate for students from lower-income areas. These findings are in line with the "discouraged student" effect theorised, but not confirmed, by Micklewright *et al.* (1990): prospective students interpret a current weak local labour market as a negative indicator of future job prospects. Hence, they respond by not entering university education, opting to join the labour force at the next available opportunity.

Observing the GDHI variable, small, significant (1%) positive effects are again witnessed for lower-income areas, with a 1% increase in average GDHI resulting in a 0.205% higher entry rate for lower-income areas. These results provide evidence that lower-income households drive this relationship at an aggregate UK level. As could be expected, GDHI does not present significantly in the high-income regression: prospective students likely receive money in addition to student financing (e.g. from family), plausibly eliminating income as a factor in entry decisions.

Similar to geographical analysis conducted previously, GDPWA is significant for lower-income areas. Again, recognising a potential multicollinearity issue, the lower-income regression was rerun with the GDPWA removed. Despite model fit weakening and local unemployment slightly reducing in significance (now 10% level), importantly, results continue to confirm the hypothesis and present an almost identical coefficient. In line with Micklewright *et al.* (1990), effects are shown to be sensitive to specification.

6. Robustness checks and suggestions for future analysis

Various checks were undertaken to assess the validity of the previous regressions conducted (*Table 5*). Robustness tests focused acutely on the previous England and Wales regression given the more wide-ranging impact these findings will have.

Variables	(1)	(2)	(3)
Ln_UNEMP	-0.002 (0.003)	0.002 (0.003)	
Ln_YUNEMP			-0.000 (0.003)
Ln_GDHI	0.148*** (0.050)	0.219*** (0.060)	-0.291*** (0.070)
Ln_GDPWA	-0.054 (0.033)	-0.081** (0.037)	-0.156* (0.082)
Ln_WP	0.001 (0.003)	0.006 (0.004)	0.005 (0.005)
Ln_DEGSHARE	0.006 (0.008)	-0.004 (0.010)	-0.047 (0.029)
Ln_EXAMP		0.015** (0.006)	
const.	-1.295** (0.512)	-2.074** (0.654)	-3.039*** (0.824)
Obs.	1365	1001	525
No. of NUTS3 regions	105	91	35
R-square (within)	0.786	0.813	0.860

Table 5: Robustness checks exploring the validity of previous results.

As summarised previously, whilst the COVID-19 pandemic recession led to significant drops in GDP, employment support schemes mitigated marked unemployment increases. Given the differing characteristics of this recession, column (1) restricts the panel to 2006-2019 (omitting the pandemic) to assess the effect on results. Unemployment remains insignificant, whilst GDHI

remains strongly significant (despite decreasing slightly in magnitude). Most interestingly, GDPWA becomes insignificant. Whilst further research is needed to explore this period more extensively, this could suggest that previously significant GDPWA effects were conflating other factors arising from the pandemic (e.g. the shift to virtual learning causing a reduction in those entering university).

In their respective research, Whitfield and Wilson (1991), Rice (1999), and Clark (2011) all highlight the potential importance of exam performance in entry rate decisions. Exam performance is likely to be determined by wider factors also affecting enrolment (e.g. family background affects both exam performance and entry to university), and so coefficients would be expected to overstate the contribution this variable would have. This, combined with data limitations present (only available from 2010-2021, omitting the GFC) led to omission from the core specification. To assess any potential impact, Column (2) now introduces an exam performance variable, sourced from Department for Education data (2023), detailing the percentage of the population achieving 3 A* to A – proxying top performers who often continue into university education. Whilst results should be treated with relative caution given the factors outlined prior, exam performance is found to have significant, positive effects at the 5% level. Future analysis could address data constraints currently present, potentially including a measure of exam performance moving forward.

Previous literature also highlights that, due to more accurately representing the alternative labour market option faced if not enrolling into university, youth unemployment may have a greater influence in entry decisions (McVicar & Rice, 2001; Clark, 2011; Meschi, et al., 2018). As this variable was only available for 35 NUTS3 levels, the working-age unemployment rate was instead preferred. Substituting unemployment for the youth unemployment rate (to avoid

arbitrary serial correlation), no significant effects are present for these 35 regions over 2006-2021 (column (3)). Future work should ascertain whether this holds for wider regions.

Other limitations of this analysis that should be addressed in future research are the omission of Northern Ireland, and the inability to explore the effects of gender, ethnicity, age, and different modes of university study (e.g. full-time vs part-time), comparable to previous literature. Whilst this was attempted, data at this level is not publicly available and often inaccurate due to inadequate sample sizes. Despite endogeneity concerns not being expected to drive the negative relationship found in lower-income areas, further work should act to evidence this assumption or alternatively, attempt to identify an effective instrument to mitigate any effect.

Finally, whilst this paper explores local unemployment, variables that are invariant at the local level (e.g. the national policy environment) get subsumed into estimated time dummy variables. Whilst a standard random effects specification is deemed inapplicable for this study, future analysis could explore the use of a Mundlak-type correlated random effects (CRE) model to permit inference of these national and local level effects simultaneously (see (Mundlak, 1978) for further context).

7. Project outcomes – conclusion and recommendations

This dissertation used econometric techniques to assess the relationship between the local unemployment rate and the entry rate of 18-year-olds into university education. Estimating via least squares with time and entity fixed effects, there is no significant relationship in most instances.

Previous UK literature focuses primarily on further education and national unemployment, failing to reach unanimous conclusions regarding the direction or significance of unemployment in education decisions. Exploring the relationship for the whole UK, England and Wales only, and Scotland only, local unemployment was found to be insignificant in all regressions. Whilst this insignificance is an interesting finding, the key contribution to the literature from this study is the socio-economic analysis conducted. Local unemployment was found to have a statistically significant negative effect on the university entry rate in lower-income regions (2006-2021), directly contradicting the initial hypothesis. A 1% increase in the local unemployment rate is projected to result in a 0.7% lower university entry rate for lower-income areas. Despite having a significant effect, the magnitude of the resulting elasticity is small.

Whilst theory traditionally suggests that unemployment would act to keep students in education, mainly as the opportunity cost of pursuing additional education decreases, this study suggests that students within lower-income regions may misinterpret increased unemployment as a signal that obtaining a job in the future would be more difficult, responding instead by entering the labour market at the first available opportunity. Labour mobility could potentially explain the differing significance for higher income. As outlined by the Social Mobility Commission (2020), regional outward migration is significantly less likely when individuals hail from lower socio-economic backgrounds. Subsequently, local labour market conditions are more likely to play a

role in the decisions of 18-year-olds from poorer areas, with higher-income regions influenced more by national-level indicators.

Results also highlight the positive, statistically significant effects of GDHI on university entry, driven extensively by poorer regions throughout England and Wales. Perhaps unsurprisingly, GDHI was found to be insignificant in the university entry decisions of Scottish domiciles (where university education is 'free') and higher-income regions (where parents' ability to provide additional finance is greater). Despite student finance provision improving university accessibility for individuals from lower socio-economic backgrounds, this analysis suggests it doesn't eliminate income from influencing decisions entirely.

Limitations of this study primarily arise from difficulty in sourcing data. Looking specifically at local unemployment, Clark (2011) and Meschi *et al.* (2018) suggest that youth unemployment is more informative when modelling education enrolment decisions. This specification prefers the working-age (16-64) unemployment rate as it is available for all regions considered. Additionally, other potentially important explanatory factors were unable to be sourced and could give rise to omitted variable biases. Finally, whilst unlikely, potential endogeneity could lead to estimation bias.

Noting the above caveats, results should be of interest to policymakers targeting an improved UK education level, both during a recession and more generally. Understanding that lowerincome regions (often from the north of England) respond to changes in local unemployment will enable policy to be effectively targeted. Moreover, this study highlights that financial constraints still influence decisions within these regions. Direct provision of funding (e.g. grants) is

therefore still likely to be an effective policy-lever in inducing continued education of individuals hailing from lower socio-economic backgrounds (on average⁴).

Future research should look to build upon these findings by addressing data constraints and endogeneity concerns to reinforce the conclusions drawn. Robustness tests also highlight the potential importance of wider control measures (exam performance) and the effect of the COVID-19 recession. Further disaggregated data (not currently publicly available) could also be sourced to analyse the role of gender, ethnicity, age, and mode of study. Further analysis looking into different education options at age 18 (e.g. apprenticeships) would also be complimentary. Given various UK time-series analyses find *slightly* significant effects of <u>national</u> unemployment

on further education enrolment (e.g. (Micklewright, et al., 1990) and (McVicar & Rice, 2001)), one final recommendation is to explore a Mundlak-type correlated random effects (CRE) model, simultaneously assessing the importance of both national- and local-level effects (see (Mundlak,

1978) for further context).

⁴ Those unsuited to classroom-based study/preferring job-based learning would be unlikely to respond.

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Bibliography

Alam, K. & Mamun, S. A. K., 2016. *The relationship between labour force status and educational attainment: Evidence from a system of simultaneous equations model.* [Online] Available at: <u>https://www.sciencedirect.com/science/article/ab</u> <u>s/pii/S0313592616300157</u> [Accessed 17 March 2024].

Arellano, M., 2003. *Panel Data Econometrics*. online edn ed. Oxford: Oxford University Press.

Atherton, P. G., Lewis, D. J. & Bolton, P., 2023. *House of Commons Library*. [Online] Available at: <u>https://researchbriefings.files.parliament.uk/documents/CBP-9640/CBP-9640.pdf</u> [Accessed 17 March 2024].

Baltagi, B. H. & Griffin, J. M., 1984. Short and Long Run Effects in Pooled Models. *International Economic Review*, October, 25(3), pp. 631-645.

Baltagi, B. H. & Kao, C., 2000. Nonstationary Panels, Cointegration in Panels and Dynamic Panels: A Survey. [Online] Available at: <u>https://surface.syr.edu/cgi/viewcontent.cgi?articl</u> <u>e=1135&context=cpr</u> [Accessed 22 March 2024].

Barbu, D., 2015. *The Relationship Between Unemployment and College Enrollment and Success Outcomes*. [Online] Available at: <u>https://diginole.lib.fsu.edu/islandora/object/fsu:2</u> <u>52922/datastream/PDF/view</u> [Accessed 15 March 2024].

Barr, A. & Turner, S. E., 2013. *Expanding Enrollments and Contracting State Budgets: The Effect of the Great Recession on Higher Education*. [Online] Available at: <u>https://www.jstor.org/stable/24541681?seq=7</u> [Accessed 17 March 2024].

Becker, G. S., 1962. *Investment in Human Capital: A Theoretical Analysis*. [Online] Available at: <u>https://cooperative-</u> individualism.org/becker-gary_investment-inhuman-capital-1962-oct.pdf [Accessed 16 March 2024].

Becker, G. S. & Chiswick, B. R., 1966. *Education and the Distribution of Earnings*. [Online] Available at: <u>https://www.jstor.org/stable/1821299?seq=2</u> [Accessed 17 March 2024].

Ben-Porath, Y., 1967. *The Production of Human Capital and the Life Cycle of Earnings*. [Online] Available at: <u>https://www.jstor.org/stable/1828596</u> [Accessed 17 March 2024].

Breusch, T. S. & Pagan, A. R., 1979. A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, 47(5), pp. 1287-1294.

Britton, J., Dearden, L., Waltmann, B. & Van der Erve, L., 2020. *The impact of undergraduate degrees on lifetime earnings*. [Online] Available at: <u>https://ifs.org.uk/publications/impact-</u> <u>undergraduate-degrees-lifetime-earnings</u> [Accessed 17 March 2024].

Burgess, S. et al., 2018. *Role models, mentoring and university applications – evidence from a crossover randomised controlled trial in the United Kingdom*. [Online] Available at: <u>https://discovery.ucl.ac.uk/id/eprint/10061074/1/</u> <u>Macmillan_Article%20C%20-</u> <u>%20Sanders%20et%20al_accepted%20version.p</u> <u>df</u> [Accessed 16 March 2024].

Card, D. & Lemieux, T., 2000. DROPOUT AND ENROLLMENT TRENDS IN THE. [Online] Available at: <u>https://economics.ubc.ca/wpcontent/uploads/sites/38/2013/05/pdf_paper_tho</u> <u>mas-lemieux-dropout-enrollment-trends.pdf</u> [Accessed 15 March 2024].

Card, D. & Lemieux, T., 2001. Dropout and Enrollment Trends in the Postwar Period What Went Wrong in the 1970s?. [Online] Available at: https://www.nber.org/system/files/chapters/c106 <u>94/c10694.pdf</u> [Accessed 15 March 2024].

Christoph, B., Spangenberg, H. & Quast, H., 2024. Tertiary Education, Changing One's Educational Decision and the Role of Parental Preferences. *Research in Higher Education*, Volume 65, pp. 283-302.

Clark, D., 2011. Do Recessions Keep Students in School? The Impact of Youth Unemployment on Enrolment in Post-compulsory Education in England. [Online] Available at: <u>https://www.jstor.org/stable/41236146?seq=10</u> [Accessed 15 March 2024].

Cumbria Intelligence Observatory, 2023. *Labour Market Briefing October 2023*. [Online] Available at: <u>https://cumbria.gov.uk/elibrary/Content/Internet/</u> 536/671/4674/17217/17224/45223141658.PDF [Accessed 17 March 2024].

Davis-Kean, P. E., 2005. The influence of parent education and family income on child achievement: the indirect role of parental expectations and the home environment. [Online] Available at:

https://pubmed.ncbi.nlm.nih.gov/15982107/ [Accessed 16 March 2024].

DBIS, 2013. The Benefits of Higher Education Participation for Individuals and Society: key findings and reports "The Quadrants". [Online] Available at: https://assets.publishing.service.gov.uk/media/5a 7ba5fee5274a7318b9004a/bis-13-1268-benefitsof-higher-education-participation-thequadrants.pdf [Accessed 17 March 2024].

Dellas, H. & Sakellaris, P., 2003. *On the Cyclicality of Schooling: Theory and Evidence.* [Online] Available at: <u>https://www.jstor.org/stable/3488876?seq=13</u> [Accessed 17 March 2024].

Department for Education , 2023. *Students getting 3 A grades or better at A level.* [Online] Available at: <u>https://www.ethnicity-facts-</u> figures.service.gov.uk/education-skills-andtraining/a-levels-apprenticeships-furthereducation/students-aged-16-to-18-achieving-3-agrades-or-better-at-a-level/latest/#download-thedata

[Accessed 29 March 2024].

Desforges, C. & Abouchaar, A., 2003. *The Impact of Parental Involvement, Parental Support and Family Education on Pupil Achievements and Adjustment: A Literature Review.* [Online] Available at: <u>https://www.nationalnumeracy.org.uk/sites/defa</u> <u>ult/files/documents/impact_of_parental_involve</u> <u>ment/the_impact_of_parental_involvement.pdf</u> [Accessed 16 March 2024].

Durbin, J. & Waston, G. S., 1951. Testing for Serial Correlation in Least Squares Regression. II. *Biometrika*, 38(1), pp. 159-177.

European Parliament, 2023. Common classification of territorial units for statistics (NUTS). [Online] Available at: https://www.europarl.europa.eu/factsheets/en/sh eet/99/common-classification-of-territorialunits-for-statistics-nuts-[Accessed 15 March 2024].

Fernández, R. M. & Shioji, E., 2000. *Human Capital Investment in the Presence of Unemployment: Application to University Enrolment in Spain.* [Online] Available at: <u>https://ora.ox.ac.uk/objects/uuid:3b03550d-680a-41fd-a01d-6261f7befbcb/files/mce1f2013bea389eeb787816</u> <u>8381a8328</u> [Accessed 17 March 2024].

Freeman, R. B., 1981. *Implications of the Changing U.S. Labor Market for Higher Education*. [Online] Available at: <u>https://papers.ssrn.com/sol3/papers.cfm?abstract</u> <u>id=349094</u> [Accessed 22 March 2024].

Freeman, R. B., 1986. Chapter 6 Demand for education. *Handbook of Labor Economics*, Volume 1, pp. 357-386.

Freeman, R. B. & Katz, L. F., 1977. *The Overeducated American*. [Online] Available at: <u>https://www.nber.org/system/files/chapters/c785</u> <u>0/c7850.pdf</u> [Accessed 15 March 2024].

GOV.UK, 2022. *The Education Hub*. [Online] Available at: <u>https://educationhub.blog.gov.uk/2022/11/02/ap</u> plying-to-university-everything-you-need-toknow/ [Accessed 17 March 2024].

GOV.UK, 2024. *Repaying your student loan*. [Online] Available at: <u>https://www.gov.uk/repaying-your-student-loan/when-you-start-repaying</u> [Accessed 29 March 2024].

GOV.UK, 2024. *Student finance for undergraduates*. [Online] Available at: <u>https://www.gov.uk/student-finance/who-qualifies</u> [Accessed 15 March 2024].

GOV.UK, 2024. Student finance for undergraduates. [Online] Available at: <u>https://www.gov.uk/student-finance/new-fulltime-students?step-by-step-nav=18045f76-ac04-41b7-b147-5687d8fbb64a</u> [Accessed 29 March 2024].

Graves, J. & Kuehn, Z., 2021. *Higher education decisions and macroeconomic conditions*. [Online] Available at: <u>https://link.springer.com/content/pdf/10.1007/s1</u> <u>3209-021-00252-6.pdf</u> [Accessed 17 March 2024].

Guvenen, F. & Kuruscu, B., 2006. Ben-Porath Meets Skill-Biased Technical Change: A Theoretical Analysis of Rising Inequality*. [Online] Available at: <u>https://www.minneapolisfed.org/research/dp/dp1</u> 44.pdf [Accessed 22 March 2024].

HESA, 2024. *Higher Education Student Data*. [Online] Available at: <u>https://www.hesa.ac.uk/data-and-</u> analysis/students [Accessed 15 March 2024].

Hsiao, C., 2006. *Panel Data Analysis -Advantages and Challenges*. [Online] Available at: <u>https://papers.ssrn.com/sol3/papers.cfm?abstract_id=902657</u> [Accessed 29 March 2024].

Hsiao, C., 2006. Panel Data Analysis – Advantages and Challenges. [Online] Available at: https://deliverypdf.ssrn.com/delivery.php?ID=79 500610312402401710508109007108812110308 207104202309412009211108802909402311700 30870350130611211112005512109700509600 607904505303906209312511012210308708209 909106108306808002410902711012108201102 3001027090115 [Accessed 17 March 2024].

Jensen, R., 2010. The Perceived Returns to Education and the Demand for Schooling. *The Quarterly Journal of Economics*, Volume 1, pp. 515-548.

Kao, C., 1999. Spurious regression and residualbased tests for conintegration in panel data. *Journal of Econometrics*, 90(1), pp. 1-44.

Kodde, D. A., 1988. Unemployment expectations and human capital formation. [Online] Available at: https://www.sciencedirect.com/science/article/ab s/pii/0014292188900232 [Accessed 17 March 2024].

Levin, A., Lin, C.-F. & Chu, C.-S. J., 2002. Unit root tests in panel data: asymptotic and finitesample properties. *Journal of Econometrics*, 108(1), pp. 1-24.

Long, B. T., 2014. *The Financial Crisis and College Enrollment How Have Students and Their Families Responded?*. [Online] Available at: <u>https://www.nber.org/system/files/chapters/c128</u> <u>62/c12862.pdf</u> [Accessed 17 March 2024].

Mcintosh, S., 2001. *The Demand for Post-Compulsory Education in Four European*

Countries. [Online] Available at: https://www.researchgate.net/publication/24079 275_The_Demand_for_Post-Compulsory_Education_in_Four_European_Co untries [Accessed 16 March 2024].

McVicar, D. & Rice, P., 2001. *Binary regression model Binary regression model*. [Online] Available at: <u>https://watermark.silverchair.com/47.pdf?token=</u> <u>AQECAHi208BE49Ooan9kkhW_Ercy7Dm3ZL</u> <u>9Cf3qfKAc485ysgAAA1YwggNSBgkqhkiG9</u> w0BBwagggNDMIIDPwIBADCCAzgGCSqGS Ib3DQEHATAeBglghkgBZQMEAS4wEQQM2 tGh8nM4FdMAcEudAgEQgIIDCV11NCTd0dF pW1QqaHyflN4dQvQomyTMhNIOyACAgaj4awHGLMB [Accessed 17 March 2024].

Meschi, E., Swaffield, J. & Vignoles, A., 2018. The role of local labour market conditions and youth attainment on post-compulsory schooling decisions. [Online] Available at:

https://eprints.whiterose.ac.uk/139419/1/Meschi Swaffield_Vignoles_rev2_final.pdf [Accessed 17 March 2024].

Micklewright, J., Pearson, M. & Smith, S., 1990. Unemployment and Early School Leaving. [Online] Available at: https://www.jstor.org/stable/2234193?seq=5

[Accessed 17 March 2024].

Mundlak, Y., 1978. On the Pooling of Time Series and Cross Section Data. *Econometrica*, 46(1), pp. 69-85.

National Audit Office, 2020. *Implementing employment support schemes in response to the COVID-19 pandemic*. [Online] Available at: <u>https://www.nao.org.uk/reports/implementing-</u> <u>employment-support-schemes-in-response-to-</u> <u>the-covid-19-pandemic/</u> [Accessed 17 March 2024].

Nero, M. & Nordberg, E., 2023. *The Impact of Unemployment on Enrollment in Higher Education*. [Online] Available at: <u>https://www.diva-</u> portal.org/smash/get/diva2:1763471/FULLTEX <u>T01.pdf</u> [Accessed 16 March 2024].

Nickell, S., 1979. *Education and Lifetime Patterns of Unemployment*. [Online] Available at: <u>https://www.jstor.org/stable/1829911</u> [Accessed 22 March 2024].

Nomis, 2024. *official census and labour market statistics*. [Online] Available at: <u>https://www.nomisweb.co.uk/sources</u> [Accessed 15 March 2024].

OECD, 2022. Education at a Glance 2022: OECD Indicators. [Online] Available at: <u>https://www.oecd-</u> <u>ilibrary.org/sites/2d088c0c-</u> en/index.html?itemId=/content/component/2d08 <u>8c0c-en</u> [Accessed 17 March 2024].

OECD, 2022. *Productivity, human capital and educational policies*. [Online] Available at: <u>https://www.oecd.org/economy/human-capital/</u> [Accessed 17 March 2024].

OECD, 2023. *Education GPS*. [Online] Available at: <u>https://gpseducation.oecd.org/revieweducationp</u> <u>olicies/#!node=41761&filter=all</u> [Accessed 17 March 2024].

ONS, 2023. Graduate labour market statistics. [Online] Available at: <u>https://explore-education-</u> <u>statistics.service.gov.uk/find-statistics/graduate-</u> <u>labour-markets</u> [Accessed 17 March 2024].

ONS, 2023. Regional gross disposable household income: all ITL level regions. [Online] Available at: https://www.ons.gov.uk/economy/regionalaccou nts/grossdisposablehouseholdincome/datasets/re gionalgrossdisposablehouseholdincomegdhi [Accessed 17 March 2024].

ONS, 2023. Regional gross domestic product: all ITL regions. [Online] Available at: https://www.ons.gov.uk/economy/grossdomestic productgdp/datasets/regionalgrossdomesticprodu ctallnutslevelregions [Accessed 16 March 2024].

ONS, 2024. *Labour Force Survey*. [Online] Available at: <u>https://www.ons.gov.uk/surveys/informationforh</u> <u>ouseholdsandindividuals/householdandindividua</u> <u>lsurveys/labourforcesurvey</u> [Accessed 15 March 2024].

ONS, 2024. *LFS: ILO Unemployment rate: UK: All: Aged 16-64: %: SA*. [Online] Available at: <u>https://www.ons.gov.uk/employmentandlabour</u> <u>market/peoplenotinwork/unemployment/timeseri</u> <u>es/lf2q/lms</u> [Accessed 15 March 2024].

Oreopoulos, P., 2006. Estimating Average and Local Average Treatment Effects of Education when Compulsory Schooling Laws Really Matter. *AMERICAN ECONOMIC REVIEW*, March, 96(1), pp. 152-175.

Pesaran, M. H., 2015. Testing Weak Cross-Sectional Dependence in Large Panels. *Econometric Reviews*, 34(6), pp. 1089-1117.

Pissarides, C. A., 1982. From School to University: The Demand for Post-Compulsory Education in Britain. [Online] Available at: https://www.jstor.org/stable/2232555?searchTex t=the+demand+for+postcompulsory+education+in+Britain&searchUri= %2Faction%2FdoBasicSearch%3FQuery%3Dth e%2Bdemand%2Bfor%2Bpostcompulsory%2Beducation%2Bin%2BBritain%2 6so%3Drel&ab_segments=0%2Fbasic_search_g sv2% [Accessed 17 March 2024].

Rice, P., 1999. The impact of local labour markets on investment in further education: Evidence from the England and Wales youth cohort studies. [Online] Available at: https://link.springer.com/content/pdf/10.1007/s0 <u>01480050100.pdf</u> [Accessed 17 March 2024].

Rutledge, Z., 2018. Interpreting Regression Coeffcients. Step-by-Step Derivations and Explanations. [Online] Available at: <u>https://www.zachrutledge.com/uploads/1/2/5/6/1</u> 25679559/interpreting_regression_coefficients.p <u>df</u>

[Accessed 29 March 2024].

Sargan, J. D., 1958. The Estimation of Economic Relationships using Instrumental Variables. *Econometrica*, 3(1), pp. 393-415.

Social Mobility Commission, 2020. *Moving out* to move on. Understanding the link between migration, disadvantage and social mobility. [Online] Available at: https://assets.publishing.service.gov.uk/media/5f 1825953a6f407276e9863f/Moving_out_to_mov e_on_report.pdf

[Accessed 29 March 2024].

Taylor, M. & Rampino, T., 2014. *Educational Aspirations and Attitudes over the Business Cycle.* [Online] Available at: <u>https://onlinelibrary.wiley.com/doi/epdf/10.1111</u> /ecca.12091?saml_referrer [Accessed 17 March 2024].

Topel, R. H., 1997. Factor Proportions and Relative Wages: The Supply-Side Determinants of Wage Inequality. [Online] Available at: <u>https://www.aeaweb.org/articles?id=10.1257/jep</u>. <u>.11.2.55</u> [Accessed 15 March 2024].

Tumino, A. & Taylor, M., 2015. *The impact of local labour market conditions on school leaving decisions*. [Online] Available at: <u>https://www.iser.essex.ac.uk/wp-content/uploads/files/working-papers/iser/2015-14.pdf</u> [Accessed 17 March 2024].

UCAS, 2024. 2024 SEES MORE 18-YEAR-OLDS APPLY FOR HIGHER EDUCATION. [Online]

Available at: <u>https://www.ucas.com/corporate/news-and-key-</u> <u>documents/news/2024-sees-more-18-year-olds-</u> <u>apply-higher-</u> <u>education#:~:text=UCAS%20data%20shows%2</u> <u>0316%2C850%20UK,up%20from%2038.2%25</u> <u>%20in%202019.</u>

[Accessed 17 March 2024].

UCAS, 2024. *KEY DATES AND THE APPLICATION JOURNEY*. [Online] Available at: <u>https://www.ucas.com/undergraduate/applying-</u> <u>university/advice-parents-guardians-and-</u> <u>carers/key-dates-and-application-</u> <u>journey#:~:text=31%20January%202024%2018</u> %3A00%20(UK%20time)&text=Applications% 20can%20be%20sent%20after,ll%20give%20it %20equal%20considera [Accessed 17 March 2024].

UCAS, 2024. UCAS UNDERGRADUATE END OF CYCLE DATA RESOURCES 2023. [Online] Available at: <u>https://www.ucas.com/data-andanalysis/undergraduate-statistics-and-</u> reports/ucas-undergraduate-end-cycle-dataresources-2023 [Accessed 15 March 2024].

UCAS, 2024. UCAS UNDERGRADUATE END OF CYCLE DATA RESOURCES 2023 -Definitions. [Online] Available at: <u>https://www.ucas.com/data-andanalysis/undergraduate-statistics-andreports/ucas-undergraduate-end-cycle-dataresources-2023</u> [Accessed 15 March 2024].

UCAS, 2024. UNDERGRADUATE TUITION FEES AND STUDENT LOANS. [Online] Available at: <u>https://www.ucas.com/money-andstudent-life/money/student-</u> finance/undergraduate-tuition-fees-and-student-<u>loans</u> [Accessed 17 March 2024].

Whitfield, K. & Wilson, R. A., 1991. Staying on in Full-Time Education: The Educational Participation Rate of 16-Year-Olds. [Online] Available at: <u>https://www.jstor.org/stable/2554824</u> [Accessed 17 March 2024].