Essays in labour economics: School leaving, unemployment and retirement

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Declarations

No part of this thesis has been submitted for another degree.

Chapter 1, entitled *"The impact of local labour market conditions on school leaving decisions"*, is a joint work with my former supervisor Professor Mark Taylor. Professor Taylor's role consisted in providing guidance for the statistical analysis and in revising and improving the editing of the text. The chapter appeared as *ISER Working Paper, 2015-14 - June 2015*. Parts of the content of the chapter also appear in the Working Paper *"The effect of local labour market conditions on educational choices: a cross country comparison", ImPRovE WP 13/06 - November 2013*, of whom I am the sole author.

The other chapters in this thesis are exclusively mine.

Chapter 2, entitled "*The scarring effect of unemployment from the early ‘90s to the Great Recession*", has been previously published as *ISER Working Paper 2015-05 - March 2015*.

Chapter 3, entitled "*Retirement and Cognitive Abilities*", has been published as *ISER Working Paper 2016-06 - July 2016*.

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Summary

This thesis investigates empirically three topics related, respectively, to school leaving, unemployment and retirement. It consists of three independent research articles, accompanied by a general introduction and a conclusion section. Chapter 1 investigates the extent to which the demand for post-compulsory education of British 16-year-olds responds to local labour market conditions. The findings show that prevailing unemployment rates influence the schooling decisions of students from a less affluent family background, while students from better-off families tend to enrol in post-compulsory education irrespectively of labour market conditions. Factors associated with the family's socio economic status, such as parental tastes for education and social norms, are arguably at the base of the different behaviours. Chapter 2 analyses the persistence in unemployment incidence during the last two decades. The methodology employed allows disentangling the true state dependence from the confounding role played by observed and unobserved heterogeneity. The evidence supports that unemployment experiences "scar" British workers by compromising their future employability. The findings also suggest a countercyclical pattern of true state dependence as unemployment scars more during recessions. Chapter 3 studies the extent to which retirement influences the cognitive capital of British older workers. The analysis relies on an instrumental variable approach to address the endogeneity bias. Consistent with the "use it or lose it" hypothesis, the results suggests that retirement contributes significantly to the cognitive decline suffered at older ages by British workers. The final section of the thesis summarises the main findings of the three chapters and discusses policy implications and extensions.

Introduction

This thesis contributes to the labour economic literature by analysing three topics of great interest in the current economic climate. First, it studies the relationship between labour market conditions and enrolment in post-compulsory education in the UK. Second, it analyses the "scarring effect" of unemployment, defined as the extent to which unemployment experiences compromise workers' re-employability, and its relationship with the business cycle. Third, it investigates how retirement influences the cognitive abilities of British older workers.

The research is relevant from a policy perspective, as the overcoming of the challenges imposed by the Great Recession and the extension of working lives have been important topics in the recent UK policy agenda. Furthermore, each chapter of this thesis covers a topic inherent to one phase of people's economic life, intended as a process which starts leaving education, continues with an economically active phase, and ends with retirement. The thesis hence assumes an almost lifetime perspective, and investigates and draws conclusions on three issues which affect the different phases of a person's life.

The reminder of this section summarises the three studies. The first chapter, titled "The impact of local labour market conditions on school leaving decisions", analyses the role of prevailing labour market conditions in affecting the demand for post compulsory education in Britain. The chapter contributes to the relevant literature by investigating to what extent this relationship varies across socio-economic groups, a theme analysed by a relatively small number of studies. We find that local labour markets significantly influence the school leaving decisions of 16 year olds living in tenant households, specifically in social housing. For these groups, an increase in the local youth unemployment rates positively affects school enrolment – consistent with opportunity cost arguments – while high levels of adult unemployment discourage it. Labour markets do not significantly affect the school leaving decisions of students from better off families. Our results suggest that factors associated with the family's socio economic status, such as parental tastes for education, and social norms, outweigh economic considerations among students from higher socio economic backgrounds, who tend to enrol in post compulsory education irrespective of labour markets conditions. As labour market conditions improve after the Great Recession, our results highlight the importance of post-compulsory education being perceived as an economically attractive option, particularly among young people from lower socio economic backgrounds.

The second chapter, titled "The scarring effect of unemployment from the early '90s to the Great Recession", contributes to the literature on unemployment persistence addressing two issues of great importance in the current economic climate. First, it analyses the extent to which the experience of unemployment scarred British men during the Great Recession. Second, it provides an insight into the relation between true state dependence and the business cycle by investigating the role of local unemployment in affecting the persistence of unemployment incidence and by analysing the dynamics of unemployment scarring during the last two decades. Our results support the presence of true state dependence both during the Great Recession and in the other two sub-periods analysed, the early '90s and early 2000s. Moreover, we find evidence of a negative association between the scarring effect of unemployment and the business cycle. From a policy perspective, our findings imply that public interventions aimed at alleviating unemployment in the short term are also likely to be beneficial in the longer term.

The third chapter, titled "Retirement and Cognitive Abilities", investigates how retirement influences the cognitive abilities of British older workers. The analysis relies on an instrumental variable approach to address the endogeneity of the retirement decision with respect to the cognitive functions. The use of a novel dataset for this area of research, the execution of separate analyses for men and women and the study of heterogeneous effects of retirement across levels of education and job types constitute the main contributions of this paper to the limited UK-based literature. Consistent with the "use it or lose it" hypothesis, we show that retirement induces cognitive decline, although the relationship is weaker for women employed in routine occupations. Disregarding potentially offsetting effects on other dimensions of health, we conclude that extending the working life has a beneficial effect on the cognitive capital of older workers and that maintaining a mentally engaging and stimulating life-style during retirement contributes to the cognitive health of the mature population.

The main conclusion of the three chapters are summarised in the Conclusion section of the thesis, where extensions and policy implications are also discussed.

Chapter 1

The impact of local labour market conditions on school leaving decisions

1.1 Introduction

It is well documented that the recent Great Recession has had a considerable impact on the UK labour market, particularly among young people. For example, between 2008 and 2011 the unemployment rate among 16-21 year olds rose by more than 7 percentage points, reaching 25 percent.[1] There is increasing discussion in policy circles about the impact that high youth unemployment rates have on young people and their future careers, with concerns about whether an early experience of unemployment may leave lasting scars in terms of future labour market attachment, wellbeing and benefit dependency. These concerns led the Government to introduce a Youth Contract that was launched in April 2012 to help young, unemployed people get a job. This provides nearly 500,000 new work-based opportunities for people aged 18-24, including apprenticeships and voluntary work experience placements. These are intended to help keep young, workless people attached to the labour market.

What has received less attention in these discussions is the potential effect of labour market conditions on school leaving decisions. According to the prediction of the human capital investment model (Becker, 1962; Card and Lemieux, 2001), education decisions respond to changes in labour market conditions as these affect both the opportunity cost and the expected returns of schooling. However, it is not possible to determine a priori whether a worsening in labour market conditions increases or reduces the demand for further and higher education. As well as reducing the opportunity cost of education, a worsening of labour market conditions can either encourage schooling if this is perceived as a way to avoid future unemployment, or discourage it otherwise (e.g. Meschi et al., 2011; Petrongolo and San Segundo, 2002; Micklewright et al., 1990; Kodde, 1988). Changes in labour market conditions can therefore

[1] Source: 2008 and 2011 Quarterly Labour Force Survey (April-June quarter).

affect demand for post compulsory education in potentially contrasting ways, and the net effect cannot be determined a priori.

Focusing on the choice of staying at school at age 16, i.e., after completing compulsory education, in this paper we investigate empirically (i) how local labour market conditions influence the secondary schooling decisions of young people in the UK; and (ii) to what extent the responsiveness of the demand for post-compulsory education to labour market conditions varies across students from different economic backgrounds.

Previous studies have shown mixed evidence on the relationship between labour market conditions and demand for schooling (Meschi et al., 2011; Petrongolo and San Segundo, 2002). Strong evidence exists in support of family economic circumstances playing a major role in affecting children's educational achievements, either through (the lack of) credit constraints and/or because of unobserved characteristics that are associated with higher family resources - e.g., access to better schools, a school-friendly family environment, parental tastes for education (Lochner and Monge-Naranjo, 2011; Carneiro and Heckman, 2002). Despite that, our knowledge about a socio-economic gradient in response to incentives from the labour market is limited and particularly relevant in the current economic climate. Changes in labour market conditions during the Great Recession might, in fact, not only have affected the demand for schooling in society, but also be associated with a widening or a shrinking in the socio-economic gap in educational achievement.

Following Petrongolo and San Segundo (2002) and analysing data from the British Household Panel Survey (BHPS) and Labour Force Survey (LFS), we use the local youth unemployment rate as a proxy for the opportunity cost of education and the adult unemployment rates to proxy future employment expectations (and, hence, return to education). Our preferred measure of family economic background is home ownership, as the home is usually the most valuable asset held by a family and assets capture better than income the longer term family socio economic status (Nam and Huang 2009). In a different model specification, we also enrich our housing tenure definition by differentiating between home owners, private tenants and social tenants. Finally, as a robustness check, we analyse to what extent the response of the demand for post compulsory education to changes in labour market conditions varies across quintiles of equivalised household income.

Consistently across model specifications, our results show that young people from economically worse-off families respond to increases in local youth unemployment rates by increasing demand for schooling, while they respond to increases in adult unemployment rates by reducing the probability of enrolling in post compulsory education. The results are consistent with theoretical predictions by Kodde (1988). The response to labour market conditions by young people from well-off families is not statistically significant.

Although disentangling the role of credit constraints as opposed to other, longer term, factors associated with family resources goes beyond the scope of this analysis, our evidence suggests for the latter to be the most plausible explanation of the different responses to labour market incentives between young people from different socio-economic backgrounds. In particular, our results suggest that young people from worse-off families tend to assign more importance to economic considerations when choosing whether to enrol in post-compulsory education. Conversely, young people from better-off families tend to enrol irrespective of labour market conditions, arguably because of stronger family tastes for education which justify schooling even when economic considerations make it less convenient.

The paper is organised as follows: Section 1.2 introduces our theoretical framework and contains a review of the literature; Section 1.3 describes the BHPS and LFS data used in the empirical analysis and summarises the key variables of interest; Section 1.4 introduces the estimation procedure and identification strategy; results are presented in Section 1.5 while Section 1.6 concludes.

1.2 Theoretical framework and literature review

This section is organised as follows. Sub-section 1.2.1 introduces the theoretical framework that we use to analyse the relationship between labour market conditions and school leaving decisions and discusses the relevant literature. In sub-section 1.2.2 we summarise the previous findings on the relationship between family resources and schooling decisions. Sub-section 1.2.3 discusses the extent to which family resources can affect the response to labour market conditions and its implications for our work.

1.2.1 Labour markets and the demand for schooling

Economic theory suggests that an increase in the unemployment rate faced by the youths reduces the opportunity cost of schooling as, intuitively, it becomes more difficult to find a job in the event of leaving school (Meschi et al., 2011; Petrongolo and San Segundo, 2002; Micklewright et al., 1990). Hence, we expect a positive relationship between youth unemployment rates and the demand for schooling.

Under the assumption that adult unemployment rates influence future employment expectations, variations in adult unemployment rates are also expected to affect educational decisions. Kodde (1988) analyses two possible scenarios. On the one hand, an increase in adult unemployment might cause a downward shift in the relationship between future employment prospects and schooling. Intuitively, this happens if employment expectation declines constantly across levels of education. Such a shift would discourage investment in education. However, it is also possible for an increase in unemployment to reduce employment expectations more at the bottom of the education distribution than at the top. In this case, education could be seen as an enhancing factor for future employability, with a consequent positive effect on the demand for schooling (Meschi et al., 2011; Petrongolo and San Segundo, 2002; Micklewright et al., 1990). Whether the first effect, which we term the “discouraged student effect”, or the second, that for simplicity we call the “insurance effect”, prevails is an empirical question which we address by exploiting data from the British Household Panel Survey (BHPS) and Labour Force Survey (LFS).

Previous research on the influence of labour market conditions on the demand for schooling has found mixed evidence. Using time series data covering various periods between 1955 and 2005, a number of studies have shown that unemployment rates affect the demand for post compulsory education in the UK, although the effects are sometimes found to be larger for males. In particular, Pissarides (1981) and Whitfield and Wilson (1991) report a positive association between adult unemployment rates and the demand for post-compulsory education, while McVicar and Rice (2001), and Clark (2011) find that the youth unemployment rate significantly increases schooling demand. Among microdata based studies, Meschi et al. (2011) show that the demand for post compulsory education is positively associated with local youth unemployment rates; Rice (1999) shows that the demand for schooling increases with local unemployment rates primarily for males with low levels of previous education attainment. By contrast, Micklewright et al. (1990) find that school leaving rates tend to increase with regional unemployment rates, although this finding is not robust to changes in the model specification. Analysing the relationship between labour market conditions and demand for post compulsory education in Spain, Petrongolo and San Segundo (2002) use the local youth unemployment rate as a proxy of the opportunity cost of schooling and the general local unemployment rate as an indicator of weak future employment prospects. Consistent with theoretical predictions, the authors show that the demand for schooling reacts positively to increases in the local youth unemployment rates and negatively to changes in adult unemployment.

In this paper, we follow the methodology proposed by Petrongolo and San Segundo (2002) and analyse to what extent the demand for post-compulsory education responds to variations in the opportunity cost of schooling (measured by changes in youth unemployment rates) and to changes in the return to schooling (measured by adult unemployment rates). We add to previous studies by explicitly modelling the role of family resources, and in particular home ownership, in determining how young people respond to labour market incentives.

1.2.2 Family resources and children's educational attainments

Previous research has shown that family resources greatly affect children’s educational outcomes (see, among others, Cameron and Heckman, 2001; Carneiro and Heckman, 2002; Blanden and Gregg, 2004; Huang et al., 2010). This relationship is usually explained by the presence of short term borrowing constraints and/or of a strong association between family resources and longer run factors which are also likely to boost children’s academic ability and educational outcomes.

In the presence of credit market imperfections, the borrowing constraints hypothesis predicts that young people from low income families might face higher costs in accessing the resources needed to participate in post-compulsory education. The marginal cost of schooling would hence be higher for young people from constrained families, causing them to invest sub-optimally in education (Lochner and Monge-Naranjo, 2011). The second hypothesis suggests that the positive relationship between family income and educational attainment might be the consequence of long run factors associated with family resources. This theory suggests that family income is highly correlated over a child’s life cycle and that families with more resources during a child’s formative years are able to “better shape the abilities and expectations of their children, who are better able to perform at school” (Carneiro and Heckman, 2002). Hence, higher family income is associated with higher ability and expectations among children, raising their educational attainment. Examples of long term factors associated with family income include the quality of primary and secondary school attended or parental tastes for education which are then passed to their children (Carneiro and Heckman, 2002). Although a number of papers have found evidence consistent with the presence of credit constraints in the US (e.g., Kane, 1996; Belley and Lochner, 2007), several studies have failed in identifying in the presence of borrowing constraints a quantitatively relevant limitation for schooling progression in the US (e.g., Carneiro and Heckman, 2002; Cameron and Taber, 2004; Keane and Wolpin, 1997; Huang et al., 2010).

In addition to parental income, several studies suggest that parental assets are important in explaining educational outcomes. Nam and Huang (2009) suggest that assets are a good indicator of the household liquidity level since savings reduce the need for borrowing while tangible assets facilitate the access to credit by providing collateral. Moreover, the authors report that assets may be a better measure than income for socio-economic inequality and a more suitable indicator of the long term economic status of the family. As with the family income hypothesis, assets might affect schooling achievement through both a short term borrowing constraint and a long term family background perspective (Huang et al., 2010).

The home is typically the most valuable and also the most commonly held asset. Lovenheim (2011) studied the effect of housing wealth on college enrolment in the US and reports that, between 1977 and 2005, 85 percent of college attendees came from homeowner families and finds a positive effect of housing wealth on college enrolment (see also Dietz and Haurin, 2003). Beyond financial reasons, and consistent with Carneiro and Heckman's (2002) thesis on the association between family income and educational outcome, Green and White (1997) suggest several other paths through which home ownership might influence children's educational outcomes. They suggest that owning a house may improve management skills which can be transferred to the children. They also argue that home owners might monitor more their own children and those of their neighbours to prevent the values of their properties being reduced by children misconduct. However, it is also possible that children of homeowners outperform children of non-homeowners not because the parents are homeowners, but because their parents possess some unobservable attributes which make them more likely both to become homeowners and to raise successful students.

A large literature has analysed the extent to which household resources influence educational attainment in the UK. Blanden and Greg (2004) find evidence of a positive relationship between household income and post compulsory education enrolment, and similar findings can be found in Rice (1987) and Chevalier et al. (2005) among others. Using cohort survey data for 1970 and 1958 cohorts, Machin and Vignoles (2004) find evidence on the relationship between family income, parental social class and higher education achievement becoming stronger over time. Studying enrolment at higher education institutions, Chowdry et al. (2013) provide evidence in favour of an association between family socioeconomic status (SES) and educational outcomes too. However, the authors show that the impact of SES is greatly reduced when controlling for secondary school achievement. Hence, the result suggests that parental SES is particularly important at earlier stages rather than on university entry.

Home ownership has also been found to be an important determinant of school leaving decisions in the UK. Micklewright et al. (1990), for instance, show that children in owner occupied households are less likely to leave school at the age of 16, while Dearden et al. (2009) find that the introduction of the Education Maintenance Allowance had a significant impact mainly among those living in rented accommodation, suggesting that credit constraints may be important.

1.2.3 Family resources and responses to labour market conditions

A small number of articles have analysed the extent to which incentives from labour markets are heterogeneous across population groups. Among them, Smith and Naylor (2001) find that the probability of dropping out of university is positively affected by the general unemployment rate in the country of origin and that the response is significantly higher for male students from a lower social class. In their analysis of post compulsory education choices in Spain, Casquel and Uriel (2009) find that family income positively affects the probability of staying in post compulsory education, while general unemployment reduces it. The authors also show that this response is statistically significant for young people from lower income families.

In this paper we investigate the extent to which young people from different socio-economic backgrounds respond differently to changes in labour market conditions. Our results show that only young people from an economically disadvantaged background respond to changes in labour market conditions, while we do not find evidence of responses from young people from economically better-off families. In particular, consistent with the opportunity cost argument, we show that, among young people from home renting families, and in particular social tenants, an increase in the youth unemployment rate is associated with an increase in the demand for schooling. We also find evidence that the same young people are discouraged by increases in adult unemployment rates.

Differences in unobserved factors associated with family resources are likely to be the main reason for such different behaviours. On the one hand, young people from wealthier families may be less sensitive to variations in incentives from the labour markets if factors associated with family socio-economic status, such as parental tastes for education, outweigh economic considerations in their schooling decisions (e.g., students from better off-families will study even if it is perceived as less profitable from an economic point of view). On the other hand, youths from worse off families might tend to assign more weight to economic considerations, thereby responding more to changes in labour market conditions.[2] Misinformation and unawareness

[2] The finding is consistent with the sociological literature summarized in Brand and Xie (2010). The authors report that social norms make college enrolment a “socially expected outcome” for individuals from a higher socio-economic group, while economic considerations play a more important role for youths from less advantaged groups.

about the real costs and benefits of education are possible causes of such differences (see Oreopoulos and Dunn, 2013 and papers cited therein).

What about credit constrains? Cameron and Taber (2004) develop a theoretical model which allows to predict how young people from affluent and poorer families would react to changes in opportunity cost and direct cost of education if differences in family resources were only capturing heterogeneity in borrowing constraints but not in tastes for schooling. In particular, the model predicts that responses to changes in the opportunity cost will be the same across constrained and unconstrained individuals, while young people from constrained families display a greater response to changes in the direct costs associated with education (see also Lochner and Monge-Naranjo, 2011). The model does not allow to predict *a priori* whether young people from borrowing constrained families would respond more or less to changes in the expected return to schooling.[3]

Since our results show no significant response from youths from better off families to changes in youth unemployment rates, while opportunity cost arguments significantly apply to youths from worse off families, we can infer that unobserved factors associated with family resources drive the different response to changes in labour market conditions across the two groups. However, we leave for future research further investigations into the role played by borrowing constraints as opposed to factors associated with family resources, as this lies outside the scope of this paper.

A further point needs to be clarified here. Assuming that both young people from better-off and worse-off families respond to changes in labour market conditions, we expect for changes in the

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[3] The model predicts that both constrained and unconstrained individuals will respond to changes in the return to schooling, but there is uncertainty on which group experience the strongest response. For given values of the parameter measuring the utility curvature, and for a sufficiently low direct cost of education, it can be shown that response from unconstrained youth is smaller than the response from constrained youth. The opposite is otherwise true.

opportunity cost of education to increase the demand for schooling. But why should an increase in adult unemployment rate discourage post compulsory school enrolment among the less advantaged students? In the framework first proposed by Kodde (1988), increases in future unemployment expectations can enhance or discourage investments in education depending on whether more schooling is expected to enhance employability. Irrespective of whether borrowing constraints or factors associated with family resources drive differences in the demand for schooling, on average students from worse-off families will arguably expect to reach a lower level of education than students from richer families. Under the assumption that the enhancing effect of extra education on future employability increases with the years or quality of extra education (i.e., the difference in employment probability between studying for 11 against 10 years is smaller than the one expected between 15 and 10 years) we can expect the "discouraged student effect" to prevail among students from worse off economic backgrounds, while the opposite could be true for students from more affluent backgrounds.

The next section introduces the data and the variables used for the empirical analysis.

1.3 Data and descriptive statistics

We use data from the British Household Panel Survey (BHPS) and the UK Labour Force Survey (LFS) to disentangle the relationship between local labour market conditions and participation in non-compulsory education.[4]

The BHPS is a panel survey launched in 1991 which surveyed people annually for 18 waves until 2008. Originally designed as a nationally representative random sample of the population of

[4] University of Essex, Institute for Social and Economic Research (2010a), Office for National Statistics, Socio-Economic Division and Northern Ireland Statistics and Research Agency (2008a,b,c,d,e,f); Office for National Statistics, Social and Vital Statistics Division (2008a, b, 2010); Office for National Statistics, Social and Vital Statistics Division and Northern Ireland Statistics and Research Agency (2008a,b,c,d,e, 2009, 2010a,b); Office of Population Censuses and Surveys, Social Survey Division (2004).

Great Britain living in private households, the original BHPS sample evolved over time through the incorporation of a sub-sample of the original UK European Community Household Panel (ECHP) sample from 1997-2001, of Scotland and Wales extension samples from 1999, and of a Northern Ireland sample in 2001. All household members aged 16 and over were usually (re)interviewed between September and December of each year, with information collected about their incomes, education, social and parental backgrounds, labour market status, job characteristics, housing tenure and other aspects of their life (Taylor et al., 2010). Since 1994 a module known as British Youth Panel collected information on youths aged 11-15 living in sampled households through a self-completion questionnaire.

Together with a range of other individual and household characteristics, these data allow us to identify 16 year olds who, when interviewed in the autumn/winter of a particular year, had recently made the decision of whether or not to remain in post-compulsory education. We identify those who remain in post-compulsory education as those who were aged 16 in August of that year and who were in full-time education at the date of interview. Those who were aged 16 in August of that year and were not in full-time education are defined as school leavers. [5]

Our focus is on the impact of labour market conditions on the school leaving decision. We capture labour market conditions using regional unemployment rates derived from the UK Labour Force Survey (LFS). The LFS is a nationally representative survey of households living at private addresses in the UK and collects data on a wide range of individual and household characteristics, with a particular focus on employment status, job characteristics and education. Conducted for the first time in 1973, the survey was carried out every two years until 1983,

[5] We identify young people who have recently made the choice using their month and year of birth. In Britain, children must remain in full-time education up until the last Friday in June in the academic year of their 16th birthday. Therefore BHPS respondents in wave 1, who were interviewed during the 1991/1992 academic school year, would have been making the school-leaving decision in June 1991 if born between September 1974 and August 1975. Those born before September 1974 would have already been aged 16 in June 1990 and so would have made the decision in the previous year, while those born after August 1975 would have made the decision in June 1992.

annually between 1984 and 1991, and quarterly since 1992.[6] We use these data to construct gender-specific ILO unemployment rates among 16-21 year olds and 40-64 year olds in each metropolitan region of the UK in the spring quarter of each year.[7] We match these to the BHPS data by gender, region and year of interview. We use data for the spring of each year for two reasons. Firstly, this is likely to be the period of the year when pupils make decisions about their educational choices for the next academic year. Secondly, in the spring quarter the respondents are still in full time education and therefore the youth unemployment rate used in the analysis is not affected by the choices made by the relevant cohort.

Figure 1.1 plots the school leaving rates for each year of the BHPS together with the average prevailing youth and adult unemployed rates. The school leaving rate is defined as the number of young people eligible to leave school in the preceding June and who were not enrolled in full time education at the time of the BHPS survey over those who were eligible to leave school. This highlights a clear downward trend since 1999, from a school leaving rate of 35 percent in 1999 to approximately 20 percent since 2006, consistent with the increase in participation in post-compulsory education in Britain. However, the school leaving rate is much less stable in earlier years, varying from 40 percent in 1991 to below 20 percent in 1995. This fluctuation between 1991 and 1999 is likely to be caused by both the emergence from the recession of the early 1990s, and also to relatively small sample sizes in years prior to 1999 when Scotland and Wales extension samples were introduced.

The trend in the average regional and gender specific 16-21years old unemployment rate decreases between 1993 and 2004, and increases after that. A negative relationship seems to emerge when compared with the school leaving rate: when youth unemployment increases, the

[6] See ONS (2007) for more information.
[7] Second quarter (Apr-June) since 2006, when calendar quarter replaced seasonal quarter. The exception is for 1991, when the data were collected on an annual basis rather than quarterly. The choice of using 16-21 is the consequence of a tradeoff between the strength of the “peer effect”, i.e., it would be better to use a more strict definition of youth unemployment rate, number of observations in the LFS and correlation with adult unemployment rate.

school leaving rate seems to decrease, and vice versa. If confirmed, this would be consistent with youth unemployment reducing the opportunity cost of education. The average regional and gender specific 40-64 years old unemployment rate faced by young people choosing whether to participate in further education shows a declining trend between 1993 and 2004 while it is stable until the end of the analysed period.

In Table 1.1 we provide some descriptive statistics for the variables used in the analysis, both for the sample of interest and separately by whether or not the respondent was a school leaver or stayed in full-time education. The final column contains the p-value of the t-test for equality of means between those observed to leave education (leavers) and those staying in further full-time education (stayers). This shows that both youth and adult unemployment rates are positively correlated with leaving school at age 16. The average youth unemployment rate faced by school leavers is 15.8 percent, compared with 15.3 percent for those remaining in post-compulsory education, while the adult unemployment rates are 4.4 percent and 4.0 percent, respectively.

Large differences between the two groups emerge in the proportions of young people living in renting households - 41 percent of those who leave education at the age of 16 live in renting households compared with 22 percent of those who remain in full-time education. This distinction is most apparent among social tenants – 35 percent of school leavers are social tenants compared with 17 percent of stayers. Young people who leave school at the age of 16 are also significantly more likely to be in lower income households. For example, the proportion of school leavers in the lowest quintile is 33 percent, while for stayers it is 22 percent. The opposite happens for the richest quintile: 14 percent of the stayers come from families who are in the top 20 percent of the income distribution, while this applies to only 5 percent of the school leavers.[8] Families with higher incomes are more able to invest optimal amounts into the education of their

[8] Household Income is equivalised using the modified OECD scale, which assigns a weight of 1 to the household head, 0.5 to other adults and 0.3 to each child under the age of 14.

children or might provide them with a more appropriate learning environment (Carneiro and Heckman, 2002; Mayer, 1997). Moreover, previous studies show that parental income significantly affects educational attainment and explains the intergenerational transmission of disadvantage (Shavit and Blossfeld, 1993), while parental wealth and socioeconomic status is positively associated with higher educational aspirations and expectations among children (Chowdry et al., 2011; Ermisch et al., 2001; Gregg and Washbrook, 2011).

Consistent with previous literature on the intergenerational transmission of cognitive abilities, there is a high correlation between parental education and young people's decisions to participate in post-compulsory education (Anger and Heineck, 2010; Black et al., 2009; Bjorklund et al., 2007). Among those observed to stay in further education, the proportion of people with parents with ISCED level smaller than 2 (Lower secondary or less) is significantly higher among leavers (67 percent) than among stayers (42percent).On the other hand, the proportion of stayers with maximum parental education higher than ISCED level 5a (Degree or more) is 19 percent, a level significantly higher than the 5 percent for school leavers.

According to previous studies, girls exhibit more positive educational aspirations and attitudes than boys (Taylor and Rampino, 2014; Rampino and Taylor, 2013), and, consequently, will have higher staying-on rates. This is reflected in our data, with 57 percent of school leavers at age 16 being boys, compared with 46 percent of those who remain in full-time education. Furthermore, we find that young people who drop out of school at age 16 are significantly more likely than those who remain in full-time education to have an unemployed parent (7.5 percent compared with 4.8 percent).

We also find very large and statistically significant differences between leavers and stayers in the number of GCSEs obtained with grades A^{*}-C or Scottish Standard Grade (STGR) obtained with grades 1 or 2 (Meschi et al., 2011; Rice, 1999). For example, the proportion of people with no good passes in such examinations is 54 percent among school leavers and 19 percent among remainers. Of course, this strong relationship is at least partly endogenous, as young people who have already decided to leave full-time education have little incentive to do well in their exams.

In light of the descriptive evidence presented in this section, three main advantages explain the choice the BHPS as the underlying dataset for our analysis. First, as discussed, the wealth of information contained in the Survey allows to control for the main determinants of the school leaving decisions. Second, the length of the time period covered in a largely consistent manner by the BHPS represents a clear advantage for the study of the relationship between labour market conditions and demand for schooling. The identification of the effects of interest benefits, in fact, from the high degree of heterogeneity in the prevailing labour market conditions between 1991 and 2008. Specifically, the early 90s crisis was followed by a period of favourable labour market conditions between the end of the 90s and the beginning of the 2000s, and by the early phase of the Great Recession in 2008. Third, the panel dimension of the BHPS and the British Youth Panel (BYP) allows retrieving information on the educational aspirations of the 16 years olds recorded at age 12. As explained in detail in section 1.5.3, we make use of educational aspiration to check the robustness of our findings.

In this context, we argue that these advantages largely overcome the limitations of the Survey, namely i) a relatively small sample size, which does not allow to analyse males and female separately; ii) the lack of information on ability or schooling achievement measured at earlier stages than the GCSE/Scottish Standard Grades; iii) the lack of a school identifier, which could have allowed to control for school quality effects.

In the remainder of the paper we examine within a multivariate framework the descriptive evidence reported in this section.

1.4 Estimation strategy and model specification

The aim of this research is to identify how local labour market conditions affect the demand for post compulsory education, explicitly controlling for the role of family resources, and home ownership in particular. The dependent variable in our analysis is dichotomous, taking the value of one if the youth leaves full-time education at the age of 16, and zero if (s)he remains in education. As described in the data section, this is identified soon after the end of the final year of compulsory schooling. We therefore estimate a series of binary dependent variable models of the following form:

$$pr(D_i = 1 | x, R, U) = pr(\alpha_1 + \alpha_2 x_i + \alpha_3 U_i + \alpha_4 R_i + \alpha_5 R_i \times U_i + \varepsilon_i > 0) \quad (1)$$

where D_i = 1 if the young person *i* left school at age 16, and = 0 if (s)he remained in full-time education, x_i is a vector of individual and household characteristics, U_i captures local labour market conditions, and the α are vectors of coefficients to be estimated. We assume that the error term ε_i is logistically distributed, and so estimate equation (1) using a logistic regression, although we also present estimates from a linear probability model for our preferred models specification.

The key explanatory variables of interest are captured by U_i. We use quarter, gender and region-specific unemployment rates to capture business cycle effects and the strength of the local labour market. We distinguish between youth unemployment rates (unemployment among 16-21 year olds) and adult unemployment rates (40-64 year olds). The former captures the immediate prospects of the young person gaining employment if exiting school at age 16, and the expectation is that high levels of current youth unemployment reduces the opportunity cost of remaining in education as it reduces the probability of finding a job. Hence, we expect this to have a negative impact on the probability of leaving education at age 16. We use the year, gender and region-specific adult unemployment rate to capture the expectation of future employability.

It is more difficult to predict the direction of the impact of adult unemployment. As reported by Kodde (1988) and Micklewright et al. (1990) among others, it is not possible to determine, *a priori*, the direction of the impact of adult unemployment. It is possible that a higher adult unemployment rate discourages investment in further education if the extra education is not expected to improve future employability, but it also possible for education to be seen as a way to escape future unemployment. In the former case, the return to education would be negatively affected by adult unemployment while in the latter case it would be positively affected.

R_i measures family resources. In our base specification this is measured by the housing tenure of the family. If, on the one hand, home owners could be less affected by borrowing constraints, living in a home owning family is also associated with factors like higher permanent income, better home learning environment, better schooling, and higher family educational expectations (Carneiro and Heckman, 2002). In our base specification, we test the extent to which home ownership influences the way labour market incentives affect educational decisions by interacting the two measures of unemployment with housing tenure. We anticipate home ownership playing a key role in the school leaving decision, either due to credit constraints or other unobservable factors associated with parental assets and educational decisions.

In a second model specification, we further distinguish between people living in privately rented accommodation and those in social housing, given that private tenants are likely to be different from social tenants. We also check the robustness of our findings to the use equivalised household income quintiles as the measure of family resources interacted with unemployment rates. Despite being more volatile than housing tenure and worse at capturing longer term socio-economic status of the family (Nam and Huang, 2009), family income is the most widely used measure of family resources. Moreover, it is possible that some homeowner families could actually be credit constrained if they are paying for a mortgage, while family income does not suffer from this problem.

We include a range of other individual and household level characteristics into the models. These include parental education, current parental unemployment and household income, which are known to be strongly correlated with educational choices (Micklewright, 1989; Micklewright et al., 1990; Petrongolo and San Segundo, 2002; Blanden and Gregg, 2004). Other control variables include gender, whether or not the respondent has moved away from the parental home, and other indicators of family composition such as whether the respondent has younger or older siblings.

We also include previous educational attainment, via the number of GCSEs obtained with grades A^*-C or Scottish Standard Grades obtained with grades 1 or 2. As well as capturing academic ability, these are likely to be strongly correlated with family resources. In particular, existing evidence on the relationship between family resources and educational outcomes shows that better off families are able to raise more academically able children because they are able to invest more in education throughout the child's life (i.e., Cameron and Heckman, 2001; Carneiro and Heckman, 2002). Also, educational attainment has been shown to play a key role in determining participation in non-compulsory education (Meschi et al., 2011; Rice, 1999), and evidence exists in the literature of a positive correlation between children's educational attitudes, aspirations and expectations and their subsequent education-related attainments and behaviour (Andrews and Bradley, 1997; Chowdry et al., 2011; Duncan et al., 1972; Khoo and Ainley, 2005; Sewell et al., 1980; Strand, 2007).

Regional and year dummies are also included in the regressions to capture the effects that are fixed across years for a given region or across regions for a given year. All standard errors are clustered at the regional level.

1.5 Estimates

In this section we present and discuss estimates from our models. First, we focus on differences between young people living in home-owning families and those living in renting families. We then further distinguish between social tenants and private renters as the latter are likely to be a very heterogeneous group, while those in social housing are likely to face the greatest borrowing constraints and have the fewest family resources.

1.5.1 Home ownership

Table 1.2 reports the estimated coefficients from logistic regressions where the dependent variable takes the value 1 if the young person left education at age 16, and 0 if (s)he remained in full-time education at the end of compulsory schooling. We estimate four different specifications. Model (1) includes unemployment rates and home ownership among the regressors, but it excludes their interaction terms. Model (2) augments Model (1) by including measures of previous education attainment of the child. As this is likely to be influenced by longer term family resources, by controlling for previous educational attainment we control whether housing tenure continues to play a role in educational choices (Cameron and Heckman, 2001). In Model (3) we include interactions between unemployment rates and housing tenure, allowing for different responses to changes in unemployment rates between home owners and tenants. Model (4) contains the same specification as Model (3), but is estimated by a linear probability model.

The coefficients reported in Column (1) of Table 1.2 show that both youth unemployment and adult unemployment rates have a negative but not statistically significant impact on the school leaving decision at age 16. Consistent with previous studies (e.g., Micklewright et al., 1990), we find that young people living in families that do not own their home are significantly more likely to leave school. Children from higher income families are also less likely to leave school at age

16 (e.g., Blanden and Gregg, 2004). The estimates on the other controls are also consistent with previous research. We find, for example, that young men are more likely than young women to leave school at age 16 (Petrongolo and San Segundo, 2002). We also find strong, negative associations between parental education and the probability of leaving school at age 16, with children from less educated parents more likely to leave than those from highly educated parents (see also Micklewright, 1989).

Average marginal effects from Model (1) are reported in the first panel of Table 1.3, and show that the effect on youth unemployment is negative and at the margin of statistical significance, with a 1 percentage point increase in youth unemployment rate reducing school dropout by 0.4 percentage points. Although weekly significant, the result is consistent with youth unemployment capturing the opportunity cost of schooling. The marginal effect on adult unemployment is also negative, but it is not statistically different from zero. Finally, consistent with Micklewright et al. (1990) among others, young people from home-renting families are 9 percentage points more likely to leave school at age 16 than young people from home-owning families.

Model (2) introduces a control for previous educational attainment measured as the number of good passes in GCSE or Scottish Standard Grade exams. Analysing the estimated coefficients reported in Column (2) of Table 1.2, it emerges that school leaving probabilities are significantly correlated with previous education attainment, with the most successful students significantly more likely to enrol in further education than less successful ones (Meschi et al., 2011; Rice, 1999). Moreover, compared with estimates relative to Model (1), it should be noted that the coefficient on housing tenure decreases in size and becomes statistically significant only at the 10 percent level, while the coefficients on household income quintile lose their statistical significance.

Marginal effects reported in Panel 2 of Table 1.3 confirm the negative, although weekly significant, effect of youth unemployment rate on school leaving probabilities, with a one percentage point increase in youth unemployment leading to a 0.4 percentage points reduction in the probability of leaving school at age 16. Average marginal effects also show that those with 1 to 4 good passes at GCSE or Scottish Standard Grade are 11.6 percentage points less likely to leave school at the age of 16 than those with no passes. For those with 5 to 9 good passes the probability of leaving school at 16 is 30 percentage points lower, while those with 10 or more passes have a probability of leaving school that is 39 percentage points lower than those with no passes. More importantly for our analysis, the average marginal effect on renting falls from 9 percentage points in Model (2) to 4 percentage points, and remains significant only at the 10 percent level. This suggests that long term family resources more than short term credit constraints explain differences in educational investment between home owners and tenants (Carneiro and Heckman, 2002).

Model (3), which represents our base specification, includes interaction terms between housing tenure and the unemployment rates. The estimates indicate that neither the youth unemployment rate nor the adult unemployment rate have a statistically significant impact on the school leaving decision when not interacted with housing tenure. The coefficient on renting, as well as those on household income, is not statistically different from zero. The coefficients on our measure of previous education attainment are large, negative and highly statistically significant, indicating that young people who attain more good GCSE/Scottish Standard Grade passes (and, hence, are more able) have a lower probability of leaving education at 16. Furthermore, we find that the prevailing unemployment rates have a statistically significant impact on school leaving decisions for young people living in rented accommodation. In particular, we find that a higher prevailing youth unemployment rate reduces the probability of leaving education at age 16, while a higher adult unemployment rate increases the probability.

Marginal effects after Model (3) are reported in Panel 3 of Table 1.3, and are in line with previous specifications. Panel 1 of Table 1.4 reports the marginal effects for the unemployment rates by housing tenure. These are computed by averaging the marginal effects on youth and adult unemployment rates among homeowners and renters separately. Results show that a one percentage point higher youth unemployment rate lowers the probability of leaving school by 1 percentage point for young people in rented accommodation. This is consistent with the youth unemployment rate capturing the opportunity cost of education, and, thus, young people in rented accommodation remaining in education when the opportunity cost of doing so is low. A one percentage point higher adult unemployment rate raises the probability of leaving school at 16 for young people in rented accommodation by 2.3 percentage points. Therefore, for those in rented accommodation, higher levels of adult unemployment reduce the expected returns of education, discouraging investments in schooling. The demand for schooling of young people from home owning families does not respond to changes in labour market conditions and for both youth and adult unemployment rates, the null hypothesis of equality of the marginal effects for home owners and tenants is rejected. Model (4) estimates Specification (3) using a linear probability model. The estimated coefficients and the reported marginal effects are highly consistent with those from our base specification and confirm our findings.

As a further check, we also compute the marginal effects of youth and adult unemployment at the median of all the dependent variables, assuming students to belong to home-owning families first and renting families later. Results are reported in Table 1.5 and are highly consistent with those reported in Table 1.4.

Consistent with previous studies, our results show that young people from tenant families invest less in education than home owners although long term family resources, through their effect on children's academic ability, explain most of the differences in school leaving decisions between the two groups. Our findings also indicate that prevailing labour market conditions do have relatively large and statistically significant impacts on the decision to enrol in post-compulsory education in Britain. However, this only emerges for young people living in families that do not own their own home. For this group, a one percentage point increase in the youth unemployment rate is predicted to reduce the probability of leaving school at age 16 by 1 percentage point, while an increase of one percentage point in the adult unemployment rate is predicted to increase the probability by 2.3 percentage points. Young people from renting families thus invest more in post-compulsory education if the prevailing labour market conditions indicate that the net gains from education (the difference between the expected returns and the opportunity cost) are sufficiently large. On the other hand, young people from home owning families are not responsive to changes in labour market conditions. Differences in factors associated with family resources such as parental tastes for education or social norms are a possible explanation for this different behaviour. If young people from better off families might choose to study irrespective of labour market conditions, young people from worse off families tend to do so when it is economically beneficial.

In the next sub-section we further investigate the role of housing tenure in affecting the response to local labour market conditions by distinguishing between young people living in home-owning families, those in social housing, and private tenants. Private renters are in fact likely to be a very heterogeneous group, while young people from households who live in social housing are both more likely to be credit constrained and to have a permanently lower level of family resources.

1.5.2 Social housing

Models (5) to (8) extend the models presented in the previous subsection by differentiating between home owning, privately renting, and social tenant households. The estimated logit coefficients from this set of models are reported in Table 1.6, with average marginal effects in

Table 1.7 and the marginal effects on unemployment rates for those living in social housing, private tenants and home owners reported in Table 1.8.

The models estimated follow those presented in Table 1.2. Model (5) includes housing tenure and unemployment rates, but excludes their interaction, and the estimated coefficients show that young people from privately renting families and those in social housing are more likely than those in home owning families to leave school at age 16. The estimated coefficients on the youth and adult unemployment rates are negative and not statistically significant. Consistent with the opportunity cost argument and with findings from Model (2), average marginal effects show that an increase in youth unemployment has a negative and weakly significant negative effect on school leaving probabilities. The average marginal effect on adult unemployment is negative but not statistically significant, while both young people from private and social renting families are significantly more likely to leave school at age 16 than home owners.

Consistent with findings from Model (3), the introduction in Model (6) of previous academic achievements as a control captures most of the effect of housing tenure, which becomes not statistically significant.

Model (7) introduces the interaction between unemployment rates and housing tenure. They indicate that only young people from social housing respond to labour markets. In particular, and consistent with what we found for all renters in Section 1.5.1, a higher youth unemployment rate is associated with a lower probability of leaving school at age 16 for young people in social housing, while a higher adult unemployment rate is associated with a higher probability of leaving education. These results confirm the propensity of the most disadvantaged group, those living in social housing, to respond to incentives from the labour market.

A comparison of the marginal effects of the youth and adult unemployment rates between young people from different housing tenures is reported in Table 1.8. These show that only those from social housing significantly respond to the youth unemployment rate, with a 1 percentage point higher unemployment rate leading to a lower probability of leaving school at age 16 by 1.1 percentage points. A test of the equality of the estimated marginal effects rejects the null hypothesis of equality between those living in social housing and home owners, while the null hypothesis of equality cannot be rejected when comparing the impact of youth unemployment on social tenants with private tenants. Young people from families in social housing are also the only group to respond to changes in adult unemployment, with an estimated marginal effect of 3.1 percentage points for a 1 percentage point higher adult unemployment rate. A test of the equality of marginal effects between those in social housing and both home owners and private tenants is rejected at the 1 percent and 5 percent levels, respectively. This suggests a different response between the most disadvantaged group, i.e., those living in social housing, and the rest of the population.

Similarly to the previous section, in Table 1.9 we also report marginal effects on youth and adult unemployment rates at the median of all the dependent variables, assuming students to belong to the three housing tenure categories in turn. Results are highly consistent with those reported in Table 1.8.

From this we conclude that renters are a highly heterogeneous group. Among them, social tenants are both more likely to leave school at age 16, although this is largely explained by a child's academic ability, and are most responsive to labour market incentives.

1.5.3 Robustness checks

We conduct a number of robustness checks. First, we test the extent to which responses to labour market conditions vary across quintiles of the income distribution. Despite housing tenure being more likely than income to capture factors associated with the longer term socioeconomic status of the family, income is the most widely used measure of family resources and it does not suffer from the problem that some home owners, who are expected to be less credit constrained than non-home owners, might, in fact, be constrained if still paying a mortgage.

We modify our model by replacing the interaction terms between housing tenure and unemployment rates in Models (3) and (4) with interaction terms between unemployment rates and equivalised household income quintiles (M9 and M10-LPM). Estimated coefficients after the logit specification are reported in Column (1) of Table 1.A1, while estimates from the linear probability model are reported in Column (2). In both cases the coefficients on the non-interacted unemployment rates, which capture the response to local market conditions for the poorest quintile of the income distribution, are statistically significant. The sign is negative for youth unemployment rate, which is consistent with the opportunity cost argument, while the sign on the coefficient on adult unemployment is positive, which, within our theoretical framework, indicates that young people from the lowest quintiles of the income distribution tend to be discouraged by increases in unemployment expectations. The interaction terms between unemployment rates and household income quintiles are statistically significant too, at least for students from families belonging to the third quintiles or above, and they tend to counterbalance the effect on the non-interacted unemployment rates (i.e., they are positive for interactions with youth unemployment rates and negative for interactions with adult unemployment rates).

Average marginal effects are reported in Table 1.A2, and are in line with those reported in Table 1.3. Table 1.A3 reports the average marginal effects on youth and adult unemployment rates by quintile of household equivalised income. Consistent with the findings of previous sections, these results confirm that young people from the lowest quintile of the income distribution react to an increase in youth unemployment rates by increasing demand for education, while they react to an increase in adult unemployment rates by reducing that demand.

Secondly, thus far we have captured previous educational attainment by the number of good passes at GCSE level. However, this might be endogenous as the timing of the exams almost overlaps with decision of staying in further education. Consequently, pupils may choose the effort to put into studying for the exams depending on their perceived probability of accessing further education. Ideally, this endogeneity problem would be solved using a different measure of ability, with respect to the timing of the assessment (e.g., at age 11) and/or its nature (e.g., cognitive abilities measured in a context unrelated to school performance). Although neither of these is available in our data, we examine the robustness of our estimates by using another source of information that is likely to capture the effect of long term family resources on a child's academic ability. Specifically, we use the preferences of the child towards further education as revealed at the age of 12.

All young people aged 11-15 living in sampled households completed a self-completion questionnaire since 1994 known as the British Youth Panel (BYP). Similar to Taylor and Rampino (2014), we use the BYP to measure young people's aspirations for participating in further or higher education through their responses to the question "Do you want to leave school when you are 16, or do you plan to go on to sixth form or college?", which was asked of all 11-15 year olds between wave 4 (1994) and wave 18 (2008). We use responses to this question when the young person was aged 12, chosen as a trade-off between sample sizes, awareness and endogeneity. The younger the age at which we use preferences, the less likely the response is to be endogenous to subsequent educational performance and decisions. At the same time, however, the less likely respondents are to be aware of the importance of future educational choices and the smaller the sample size for which we have data on actual school leaving decisions – as respondents need to remain in the sample for more years to have their actual behaviour observed. For example, twelve year olds will need to remain in the sample for four further years in order to observe whether or not they leave school at age 16, and we have matched expectation/actual choice data only from 1998 onwards (e.g., when the 12 year olds in 1994 decided whether to participate or not in further education).

We therefore modify our preferred Model Specification (3) by replacing our measure of previous academic achievement with education expectation measured at the age of 12 (M11). Model estimates are reported in the first column of Table 1.A4, and average marginal by housing tenure in Table 1.A5. Estimates show that education expectations are strongly correlated with the school leaving probability, with those expecting to leave school at age 16 more likely to actually leave it. This is consistent with an extensive previous literature highlighting the association between preferences, attitudes and aspirations and subsequent outcomes (Andrews and Bradley 1997; Chowdry et al., 2011; Duncan et al., 1972; Khoo and Ainley, 2005; Sewell et al., 1980; Strand, 2007). Despite a reduction in the significance level of our estimates caused by the loss in sample size due to not having data for waves 1-7, results confirm our main findings that an increase in youth unemployment rate is associated with an increase in the demand for schooling among young people from renting families, who are also discouraged by increases in adult unemployment rates.

Thirdly, we re-estimate our baseline model specification excluding the boost samples and only focusing on the original Essex Sample (M12). Estimates and marginal effects are reported in Panel 2 of Tables 1.A4-1.A5 and are consistent with our main findings, although the average marginal effect on youth unemployment rate among non-home owners becomes slightly smaller and at the margin of statistical significance. The drop in estimation sample, which loses a third of the total number of observations, is likely to explain this.

1.6 Conclusions

In this paper we have examined the relationship between the demand for post compulsory education and prevailing labour market conditions in Britain. This follows approaches adopted by Petrongolo and San Segundo (2002), among others, and identifies the extent to which youth and adult unemployment rates affect school leaving decisions at age 16. It explicitly models the role of homeownership, a highly valuable and commonly held asset, in determining how young people respond to incentives from labour markets. Our estimates indicate that local labour market conditions matter, but only for young people from families living in rented accommodation, and in social housing in particular. For young people in rented accommodation, a one percentage point higher youth unemployment rate is associated with a one percentage point lower probability of leaving school at age 16, while a one percentage point higher adult unemployment rate raises the probability of leaving school at age 16 by 2.3 percentage points. These effects are concentrated among those in social housing.

These findings are consistent with predictions from the human capital investment model (Becker, 1962; Card and Lemieux, 2001) and can be explained by stronger preferences toward education among students from well-off families who, for factors such as different parental tastes for education or social norms, prefer to study even when it becomes less profitable from an economic perspective. On the other hand, young people from economically worse-off families take local labour market conditions into account when deciding whether or not to enrol in further education, and do so when the expected net gains are sufficiently high.

The recent Great Recession has had a considerable effect on labour markets, and unemployment rates among young people in particular have increased significantly. Unemployment rates among 16 to 21 year olds increased by 7.5 percentage points between 2008 and 2011, reaching levels exceeding 25 percent, while among people aged 40-64, unemployment increased from 3.2 percent to 5 percent over the same period. Given this, and given our estimate of how these increases affect school leaving decisions, we can extrapolate the extent to which these increases in unemployment are likely to have affected school leaving rates. According to our estimates, the increase of 7.5 percentage points in the youth unemployment rate will, all else being equal, have reduced the probability of young people in social housing leaving school at the age of 16 by 8.2 percentage points. This is due to the lower opportunity cost associated with remaining in education during periods of high unemployment. The 1.8 percentage point increase in the adult unemployment rate will, all else being equal, have increased their propensity to leave school by 5.6 percentage points due to the lower expected returns from investing in education. Hence, the net effect of these changes in the unemployment rates could be to reduce the probability of young people from social tenant families leaving school at age 16.

Therefore, it could be argued that the Great Recession has potentially had a beneficial effect on the stock of human capital through increasing participation in post-compulsory education among the most disadvantaged group. However, this has to be considered in the wider political and economic climate, which, at the time of writing, is quite different from that prevailing over the period for which these data relate.

We find that the young people who are, on average, less likely to access further and higher education are also those more sensitive to prevailing labour market conditions and their impacts on the opportunity cost and the expected returns to education. This suggests that policies aimed at helping the economy recover from the recession should further seek to increase the expected net gains from education for young people, in particular those from lower socio-economic groups. Furthermore, to ensure that levels of skills and human capital in society continue to increase, policy makers need to ensure that as the economy recovers, labour demand strengthens and unemployment rates fall (particularly among young people), pursuing post-compulsory education remains an attractive prospect.

1.7 Tables and Figures

Figure 1.1: Dropout rate over time: BHPS 1991-2008

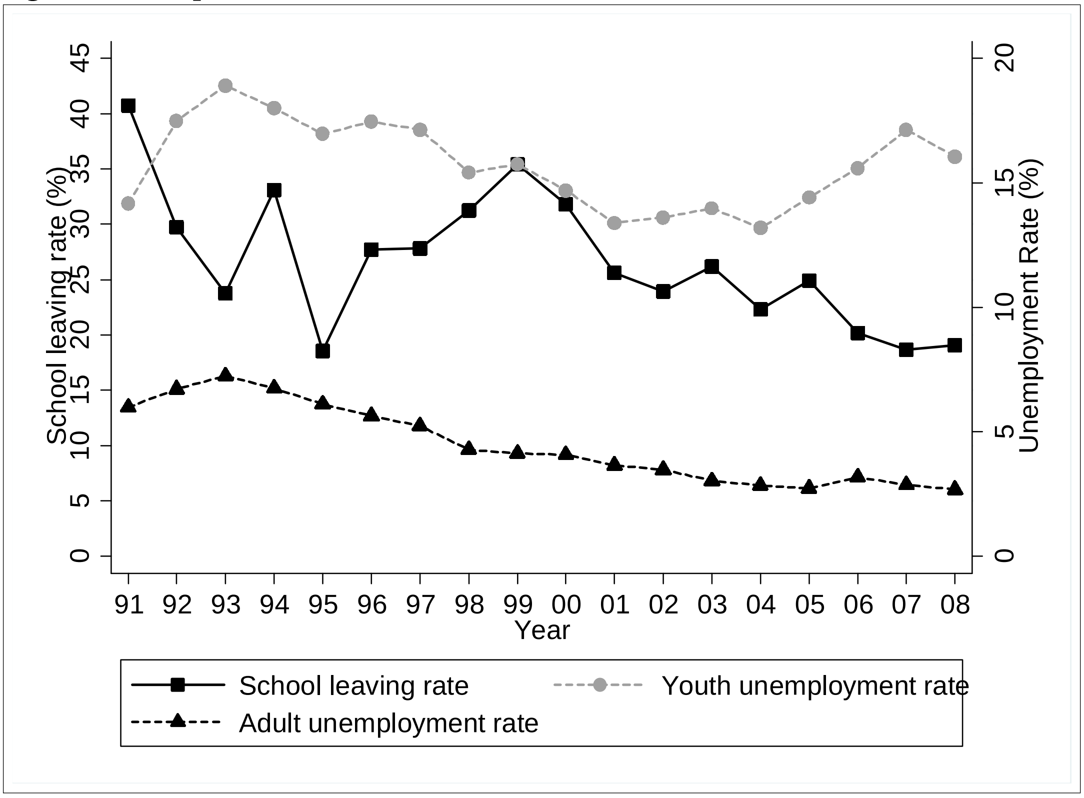

Table 1.1: Descriptive Statistics

	N	Mean	Stayers Mean	Leavers Mean	p-value (stayers=leavers)
Unemployment rate 16-21 yr-olds	4065	15.417	15.297	15.756	0.014
Unemployment rate 40-64 yr-olds	4065	4.110	4.008	4.398	0.000
Renters	3998	0.271	0.221	0.414	0.000
Social Housing	3998	0.216	0.170	0.348	0.000
Private Renters	3998	0.055	0.051	0.066	0.079
Highest observed parental education					
ISCED 0-2 / Lower secondary or less	3963	0.488	0.424	0.669	0.000
ISCED 3c-5b / Higher secondary	3963	0.360	0.387	0.283	0.000
ISCED 5a-6 / Degree or more	3963	0.152	0.189	0.048	0.000
Male	4065	0.486	0.457	0.567	0.000
Living alone	4065	0.030	0.015	0.072	0.000
Unemployed Parent	3730	0.060	0.053	0.082	0.003
GCSE A*-C / STGR 1-2 obtained					
0	3931	0.278	0.189	0.536	0.000
1 to 4	3931	0.200	0.177	0.266	0.000
5 to 9	3931	0.364	0.429	0.177	0.000
10+	3931	0.158	0.205	0.022	0.000
Eq income quintile					
1st	3986	0.249	0.220	0.330	0.000
2nd	3986	0.234	0.225	0.260	0.024
3rd	3986	0.227	0.223	0.235	0.434
4th	3986	0.173	0.193	0.117	0.000
5th	3986	0.117	0.139	0.057	0.000
Has younger sibling	4065	0.544	0.555	0.512	0.015
Has older sibling	4065	0.379	0.376	0.387	0.543

Table 1.2: Determinants of leaving school at age 16

	(1) M1	(2) M2	(3) M3	(4) M4-LPM
Youth unemployment rate	-0.025	-0.029^{*}	-0.016	-0.003
	(0.015)	(0.016)	(0.017)	(0.002)
Adult unemployment rate	-0.007	0.036	-0.014	-0.000
	(0.034)	(0.037)	(0.038)	(0.005)
Home owner (Ref.)				
Renter	0.524^{***}	0.234^{*}	0.199	0.032
	(0.133)	(0.127)	(0.220)	(0.034)
Renter:*Youth unemployment rate			-0.035^{**}	-0.006^{**}
			(0.014)	(0.002)
Renter:*Adult unemployment rate			0.137^{***}	0.025^{***}
			(0.035)	(0.008)
GCSEs grade A*-C / STGR : 0 (Ref.)				
1-4		-0.542^{***}	-0.520^{***}	-0.123^{***}
		(0.087)	(0.088)	(0.023)
5-9		-1.706^{***}	-1.692^{***}	-0.313^{***}
		(0.107)	(0.109)	(0.020)
10+		-2.926^{***}	-2.934^{***}	-0.368^{***}
		(0.184)	(0.184)	(0.023)
Household Income: 1st Quintile (Ref.)				
2nd	-0.080	-0.014	-0.024	-0.003
	(0.109)	(0.117)	(0.121)	(0.021)
3rd	-0.000	0.151	0.140	0.021
	(0.132)	(0.131)	(0.131)	(0.021)
4th	-0.382^{**}	-0.217	-0.217	-0.026
	(0.173)	(0.170)	(0.168)	(0.024)
5th	-0.519^{**}	-0.211	-0.195	-0.020
	(0.245)	(0.241)	(0.238)	(0.031)
Parental Education: less than lower secondary (Ref.)				
Higher secondary / Vocational	-0.448^{***}	-0.266^{**}	-0.269^{**}	-0.051^{**}
	(0.115)	(0.125)	(0.124)	(0.019)
Degree or more	-1.375^{***}	-0.852^{***}	-0.863^{***}	-0.098^{***}
	(0.212)	(0.236)	(0.235)	(0.027)
Male	0.730^{***}	0.488^{**}	0.482^{**}	0.071^{**}
	(0.192)	(0.214)	(0.214)	(0.031)
Lives alone	1.158^{***}	0.957^{***}	0.942^{***}	0.207^{***}
	(0.248)	(0.339)	(0.342)	(0.068)
Unemployed parent	0.133	0.025	0.016	0.004
	(0.238)	(0.261)	(0.261)	(0.049)
Has older siblings	0.183^{**}	0.111	0.116	0.016
	(0.081)	(0.078)	(0.079)	(0.013)
Has younger siblings	-0.146	-0.160	-0.164	-0.023
	(0.119)	(0.134)	(0.132)	(0.019)
_cons	-1.038^{*}	-0.551	-0.684	0.389^{***}
	(0.607)	(0.691)	(0.689)	(0.099)
Region dummies	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes
N	3635	3556	3556	3556

Estimates of M1- M3 are from logit models; estimates of M4 are from a linear probability model; standard errors in parentheses. Standard errors clustered by region. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: Average Marginal Effects, M1 to M4-LPM

	M1			M2			M3			M4-LPM		
	AME	se	pvalue	AME	se	pvalue	AME	se	pvalue	AME	se	pvalue
Youth unemployment rate	-0.004	0.002	0.091	-0.004	0.002	0.066	-0.004	0.002	0.077	-0.004	0.002	0.099
Adult unemployment rate	-0.001	0.006	0.843	0.005	0.006	0.332	0.005	0.006	0.380	0.006	0.006	0.270
Renter	0.093	0.025	0.000	0.036	0.020	0.079	0.038	0.020	0.057	0.047	0.023	0.061
GCSE A*-C / STGR 1-2												
1-4	.	.	.	-0.116	0.020	0.000	-0.111	0.020	0.000	-0.123	0.023	0.000
5-9	.	.	.	-0.301	0.019	0.000	-0.297	0.019	0.000	-0.313	0.020	0.000
10+	.	.	.	-0.392	0.023	0.000	-0.390	0.023	0.000	-0.368	0.023	0.000

Table 1.4: Effects of unemployment rates by housing tenure, M3 and M4-LPM

	M3			M4-LPM		
	AME	se	pvalue	AME	se	pvalue
Youth unemployment rate						
Home owner	-0.002	0.002	0.351	-0.003	0.002	0.308
Renter	-0.010	0.003	0.005	-0.008	0.003	0.014
Diff (R-HO)	-0.007	0.003	0.003	-0.006	0.002	0.020
Adult unemployment rate						
Home owner	-0.002	0.005	0.705	-0.000	0.005	0.934
Renter	0.023	0.009	0.009	0.025	0.009	0.016
Diff (R-HO)	0.025	0.007	0.000	0.025	0.008	0.007

Table 1.5: Effects of unemployment rates by housing tenure at fixed values of covariates*, M3

	M3		
	ME	se	pvalue
Youth unemployment rate			
Home owner	-0.003	0.003	0.366
Renter	-0.009	0.003	0.005
Diff (R-HO)	-0.007	.	0.005
Adult unemployment rate			
Home owner	-0.002	0.006	0.708
Renter	0.022	0.009	0.010
Diff (R-HO)	0.024	.	0.001

Covariates are fixed at the following values: 5 to 9 GCSE A-C / STGR 1-2;female; living with her parents; max parental education=higher secondary; parents in employment; 3rd household income quintile; no older siblings living in the household; no younger siblings living in the household; residents in south Yorkshire; wave=11

Table 1.6: Determinants of leaving school at age 16, M5 to M8-LPM

	(1)	(2)	(3)	(4)
	M5	M6	M7	M8-LPM
Youth unemployment rate	-0.025	-0.029*	-0.015	-0.002
	(0.015)	(0.016)	(0.017)	(0.002)
Adult unemployment rate	-0.007	0.037	-0.015	-0.001
	(0.034)	(0.037)	(0.038)	(0.005)
Private renters	0.359**	0.277*	0.543	0.094
	(0.162)	(0.158)	(0.748)	(0.112)
Private Renter: *Youth unemployment rate			-0.007	-0.001
			(0.061)	(0.009)
Private renter: *Adult unemployment rate			-0.045	-0.010
			(0.108)	(0.018)
Social housing: *Youth unemployment rate			-0.039***	-0.007**
			(0.014)	(0.002)
Social housing: *Adult unemployment rate			0.173***	0.033***
			(0.038)	(0.009)
GCSEs grade A*-C / STGR : 0 (Ref.)				
1-4		-0.543***	-0.520***	-0.123***
		(0.087)	(0.090)	(0.023)
5-9		-1.708***	-1.693***	-0.312***
		(0.110)	(0.117)	(0.021)
10+		-2.928***	-2.928***	-0.366***
		(0.186)	(0.180)	(0.024)
Household Income: 1st Quintile (Ref.)				
2nd	-0.074	-0.015	-0.024	-0.003
	(0.106)	(0.117)	(0.122)	(0.021)
3rd	0.006	0.150	0.143	0.022
	(0.135)	(0.132)	(0.136)	(0.022)
4th	-0.378**	-0.217	-0.212	-0.025
	(0.175)	(0.170)	(0.172)	(0.024)
5th	-0.518**	-0.211	-0.198	-0.020
	(0.244)	(0.241)	(0.238)	(0.031)
Parental Education: less than lower secondary (Ref.)				
Higher secondary / Vocational	-0.442***	-0.268**	-0.269**	-0.050**
	(0.113)	(0.122)	(0.123)	(0.019)
Degree or more	-1.354***	-0.856***	-0.852***	-0.097***
	(0.211)	(0.231)	(0.232)	(0.026)
Male	0.729***	0.488**	0.480**	0.071**
	(0.194)	(0.214)	(0.212)	(0.031)
Lives alone	1.167***	0.955***	0.949***	0.209***
	(0.259)	(0.342)	(0.340)	(0.067)
Unemployed parent	0.128	0.026	0.033	0.007
	(0.241)	(0.262)	(0.264)	(0.049)
Has older siblings	0.180**	0.112	0.120	0.017
	(0.081)	(0.077)	(0.079)	(0.013)
Has younger siblings	-0.148	-0.159	-0.170	-0.024
	(0.118)	(0.134)	(0.134)	(0.019)
Social housing	0.567***	0.224	0.117	0.018
	(0.149)	(0.151)	(0.210)	(0.033)
_cons	-1.054*	-0.548	-0.721	0.381***
	(0.612)	(0.694)	(0.719)	(0.103)
Region dummies	Yes	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes	Yes
N	3635	3556	3556	3556

Estimates of M5- M7 are from logit models; estimates of M8 are from a linear probability model; standard errors in parentheses. Standard errors clustered by region. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Marginal Effects M5 to M8-LPM

	M5			M6			M7			M8-LPM		
	AME	se	pvalue	AME	se	pvalue	AME	se	pvalue	AME	se	pvalue
Youth UR	-0.004	0.003	0.090	-0.004	0.002	0.066	-0.004	0.002	0.087	-0.004	0.002	0.112
Adult UR	-0.001	0.006	0.837	0.005	0.006	0.330	0.005	0.006	0.400	0.006	0.006	0.289
Private renter	0.062	0.030	0.038	0.042	0.026	0.098	0.039	0.027	0.154	0.039	0.026	0.154
Social Housing	0.102	0.028	0.000	0.034	0.024	0.154	0.038	0.024	0.110	0.049	0.029	0.112
GCSE A*-C / STGR 1-2												
1-4	.	.	.	-0.116	0.021	0.000	-0.111	0.021	0.000	-0.123	0.023	0.000
5-9	.	.	.	-0.301	0.020	0.000	-0.297	0.021	0.000	-0.312	0.021	0.000
10+	.	.	.	-0.392	0.023	0.000	-0.390	0.023	0.000	-0.366	0.024	0.000

Table 1.8: Effects of unemployment rates by housing tenure, M7 and M8-LPM

	M7			M8-LPM		
	AME	se	pvalue	AME	se	pvalue
Youth unemployment rate						
Home owner	-0.002	0.002	0.372	-0.002	0.002	0.336
Private Renters	-0.003	0.009	0.698	-0.003	0.008	0.707
Social Housing	-0.011	0.004	0.010	-0.009	0.004	0.019
Diff (HO-SH)	0.009	0.003	0.002	0.007	0.002	0.011
Diff (PR-SH)	0.007	0.010	0.488	0.006	0.009	0.523
Adult unemployment rate						
Home owner	-0.002	0.005	0.689	-0.001	0.005	0.913
Private Renters	-0.010	0.018	0.590	-0.011	0.018	0.546
Social Housing	0.031	0.009	0.001	0.033	0.009	0.003
Diff (HO-SH)	-0.033	0.007	0.000	-0.033	0.009	0.001
Diff (PR-SH)	-0.040	0.019	0.030	-0.044	0.019	0.030

Table 1.9: Effects of unemployment rates by housing tenure at fixed values of covariates*, M7

			M7	
		AME	se	pvalue
Youth unemployment rate				
	Home owner	-0.002	0.003	0.388
	Private Renters	-0.004	0.010	0.686
	Social Housing	-0.010	0.004	0.015
Diff (HO-SH)		0.007		0.004
Diff (R-SH)		0.006		0.615
Adult unemployment rate				
	Home owner	-0.002	0.006	0.694
	Private Renters	-0.011	0.021	0.610
	Social Housing	0.028	0.009	0.002
Diff (HO-SH)		-0.031		0.000
Diff (PR-SH)		-0.039		0.106

Covariates are fixed at the following values: 5 to 9 GCSE A-C / STGR 1-2; female; living with her parents; max parental education=higher secondary; parents in employment; 3rd household income quintile; no older siblings living in the household; no younger siblings living in the household; resident in south Yorkshire; wave=11

1.8 Appendix: Complementary Tables

Table 1.A1: Model estimates – M9 and M10-LPM

	(1) M9	(2) M10-LPM
Youth unemployment rate	-0.061***	-0.010***
	(0.017)	(0.003)
Adult unemployment rate	0.133**	0.026**
	(0.058)	(0.010)
GCSEs grade A*-C / STGR : 0 (Ref.)		
1-4	-0.538***	-0.126***
	(0.086)	(0.022)
5-9	-1.708***	-0.315***
	(0.103)	(0.020)
10+	-2.939***	-0.367***
	(0.186)	(0.023)
Household Income: 1st Quintile (Ref.)		
2nd	-0.061	-0.007
	(0.331)	(0.055)
3rd	-0.223	-0.022
	(0.282)	(0.047)
4th	0.190	0.015
	(0.438)	(0.058)
5th	-0.507	-0.039
	(0.746)	(0.091)
2st Quintile: *Youth Unemployment	0.037	0.006
	(0.027)	(0.004)
2st Quintile: *Adult Unemployment	-0.127	-0.022
	(0.078)	(0.014)
3rd Quintile: *Youth Unemployment	0.054**	0.008*
	(0.025)	(0.004)
3rd Quintile: *Adult Unemployment	-0.111*	-0.018
	(0.064)	(0.012)
4th Quintile: *Youth Unemployment	0.023	0.006
	(0.033)	(0.004)
4th Quintile: *Adult Unemployment	-0.178**	-0.033**
	(0.086)	(0.012)
5th Quintile: *Youth Unemployment	0.080**	0.011**
	(0.036)	(0.005)
5th Quintile: *Adult Unemployment	-0.217**	-0.034***
	(0.085)	(0.012)
Home owner (Ref.)		
Renter	0.243*	0.046*
	(0.129)	(0.024)
Parental Education: less than lower secondary (Ref.)		
Higher secondary / Vocational	-0.268**	-0.050**
	(0.127)	(0.019)
Degree or more	-0.878***	-0.101***
	(0.233)	(0.027)
Male	0.497**	0.074**
	(0.211)	(0.031)
Lives alone	0.963***	0.210***
	(0.345)	(0.067)
Unemployed parent	0.016	0.003
	(0.267)	(0.050)
Has older siblings	0.119	0.016
	(0.079)	(0.013)

Has younger siblings	-0.161	-0.023
	(0.137)	(0.020)
_cons	-0.559	0.406***
	(0.624)	(0.095)
Region dummies	Yes	Yes
Wave dummies	Yes	Yes
N	3556	3556

Estimates of M9 are from a logit model; estimates of M10 are from a linear probability model; standard errors in parentheses. Standard error clustered by region. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.A2: Average marginal effects, M9 and M10-LPM

	M9			M10-LPM		
	AME	se	pvalue	AME	se	pvalue
Youth UR	-0.004	0.002	0.041	-0.005	0.002	0.067
Adult UR	0.005	0.006	0.366	0.007	0.006	0.252
2nd Quintile	-0.006	0.018	0.754	-0.005	0.021	0.822
3rd Quintile	0.020	0.018	0.264	0.020	0.020	0.315
4th Quintile	-0.033	0.024	0.177	-0.027	0.024	0.262
5th Quintile	-0.027	0.033	0.400	-0.018	0.029	0.541
1-4 GCSE-STRGR	-0.115	0.020	0.000	-0.126	0.022	0.000
5-9 GCSE-STGR	-0.300	0.019	0.000	-0.315	0.020	0.000
10+ GCSE-STGR	-0.392	0.023	0.000	-0.367	0.023	0.000

Table 1.A3: Average marginal effects, M9 and M10-LPM, by income quintile

	M9			M10-LPM		
	AME	se	pvalue	AME	se	pvalue
Youth unemployment rate						
1st Quintile	-0.011	0.003	0.000	-0.010	0.003	0.004
2nd Quintile	-0.004	0.004	0.293	-0.004	0.004	0.284
3rd Quintile	-0.001	0.003	0.687	-0.002	0.003	0.451
4th Quintile	-0.004	0.003	0.159	-0.004	0.003	0.234
5th Quintile	0.002	0.003	0.608	0.001	0.004	0.901
Diff (2Q - 1Q)	0.007	0.005	0.126	0.006	0.004	0.174
Diff (3Q - 1Q)	0.010	0.004	0.017	0.008	0.004	0.083
Diff (4Q - 1Q)	0.006	0.004	0.127	0.006	0.004	0.148
Diff (5Q - 1Q)	0.013	0.004	0.001	0.011	0.005	0.037
Adult unemployment rate						
1st Quintile	0.024	0.010	0.019	0.026	0.010	0.020
2nd Quintile	0.001	0.011	0.920	0.004	0.012	0.742
3rd Quintile	0.003	0.006	0.590	0.008	0.007	0.273
4th Quintile	-0.005	0.009	0.563	-0.007	0.009	0.411
5th Quintile	-0.008	0.007	0.259	-0.008	0.008	0.326
Diff (2Q - 1Q)	-0.023	0.013	0.084	-0.022	0.014	0.141
Diff (3Q - 1Q)	-0.020	0.011	0.057	-0.018	0.012	0.136
Diff (4Q - 1Q)	-0.029	0.012	0.020	-0.033	0.012	0.012
Diff (5Q - 1Q)	-0.032	0.010	0.003	-0.034	0.012	0.009

Table 1.A4: Model estimates – M11 and M12

	(1) M11	(2) M12
Youth unemployment rate	-0.002	-0.006
	(0.024)	(0.021)
Adult unemployment rate	-0.095	-0.003
	(0.112)	(0.048)
Home owner (Ref.)		
Renter	0.155	0.111
	(0.487)	(0.306)
Renter:*Youth unemployment rate	-0.045	-0.028
	(0.042)	(0.021)
Renter:*Adult unemployment rate	0.270^{**}	0.131^{***}
	(0.129)	(0.049)
Expect to leave school at age 16: No (Ref.)		
Don't know	0.582^{***}	
	(0.135)	
Yes	1.378^{***}	
	(0.170)	
GCSEs grade A*-C / STGR : 0 (Ref.)		
1-4		-0.685^{***}
		(0.097)
5-9		-1.859^{***}
		(0.126)
10+		-3.287^{***}
		(0.265)
Household Income: 1st Quintile (Ref.)		
2^{nd}	0.134	-0.105
	(0.127)	(0.155)
3^{rd}	0.289	0.287^{***}
	(0.193)	(0.100)
4^{th}	0.011	-0.174
	(0.179)	(0.163)
5^{th}	-0.182	-0.308
	(0.333)	(0.242)
Parental Education: less than lower secondary (Ref.)		
Higher secondary / Vocational	-0.372^{***}	-0.213^{*}
	(0.143)	(0.127)
Degree or more	-0.944^{***}	-0.649^{**}
	(0.215)	(0.291)
Male	0.605^{***}	0.304
	(0.184)	(0.204)
Lives alone	1.400^{**}	1.132^{***}
	(0.588)	(0.265)
Unemployed parent	0.056	0.141
	(0.363)	(0.306)
Has older siblings	0.308^{*}	0.123
	(0.170)	(0.124)
Has younger siblings	0.093	-0.085
	(0.195)	(0.134)
_cons	-1.151	-0.534
	(1.013)	(0.743)
Region dummies	Yes	Yes
Wave dummies	Yes	Yes
N	1532	2336

Estimates of M11 and M12 are from logit models; standard errors in parentheses. Standard error clustered by region.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.A5: Average marginal effects, M11 and M12, by housing tenure

	M11			M12		
	AME	se	pvalue	AME	se	pvalue
Youth unemployment rate						
Home owner	-0.000	0.003	0.935	-0.001	0.003	0.766
Renter	-0.008	0.006	0.183	-0.006	0.004	0.099
Diff (HO-R)	-0.008	0.007	0.239	-0.005	0.003	0.112
Adult unemployment rate						
Home owner	-0.013	0.015	0.392	-0.000	0.006	0.959
Renter	0.031	0.019	0.099	0.023	0.011	0.030
Diff (HO-R)	0.045	0.020	0.028	0.024	0.009	0.006

Chapter 2

The scarring effect of unemployment from the early ’90s to the Great Recession

2.1 Introduction

Persistence in unemployment incidence is a well-documented phenomenon consisting in a higher propensity to experience unemployment at a given point in time if unemployment has occurred in the past. As pointed out by Heckman and Borjas (1980), evidence on persistence is likely to arise from two different channels. On the one hand, unemployment experiences can have a causal impact on future unemployment probability. The authors define this kind of relationship "true state dependence" and both labour supply factors, such as human capital depreciation, habituation effects or a fall in search intensity, and labour demand factors, such as negative signalling and crowding in the labour markets, are likely to be the underlying causes (Lockwood, 1991; Pissarides, 1992; Blanchard and Diamond, 1994; Clark et. al., 2001; Biewen and Steffes, 2010; Michaillat, 2012; Cockx and Picchio, 2013). On the other hand, individual characteristics, observed and/or unobserved, are likely to play a major role in explaining the propensity to experience unemployment, both at a given point in time and in the future. In that case, previous unemployment experiences would proxy such characteristics and any relationship between past and current unemployment status would therefore be spurious (Heckman and Borjas, 1980).

In this work we explore the presence of persistence in unemployment incidence during the last two decades with a specific focus on the last recession. Our working definition of scarring effect, or true state dependence, hence underlies the existence of a causal relationship between previous unemployment experiences and current unemployment status. The existence of such a relationship is highly relevant for policy makers. As reported by Arulampalam et al. (2000), if true state dependence exists, short-term policies aimed at reducing unemployment will not only affect the short term unemployment rate but also the long-term equilibrium rate of unemployment. Hence, the study of unemployment persistence is of great interest in the current economic climate: the extent to which workers have been "scarred" by unemployment experiences during the great recession is in fact relevant both to better understand the long lasting effect of the crisis and to design policies that are able to efficiently foster economic recovery.

Since the ’80s a vast literature has explored the existence of state dependence, but its evidence is ambiguous. Heckman and Borjas (1980) describe four main forms of state dependence. The authors define as Markovian dependence the situation in which a difference exists between the probability of becoming unemployed for an employed worker and the probability of remaining in unemployment for an unemployed individual in a short time interval; occurrence dependence exists when the probability of becoming or remaining unemployed is influenced by the number of previous spells of unemployment; duration dependence occurs when the probability of remaining unemployed is influenced by the length of the current spell of unemployment. Finally, authors define lagged duration dependence as the situation in which the probability of remaining or becoming unemployed depends on the lengths of previous spells of unemployment. Using data from the National Longitudinal Survey of Young Men for the years 1969-1971, and focusing on the latter three forms of state dependence, the authors find no evidence of lagged duration dependence and occurrence dependence, while they find weak evidence for the existence of duration dependence.[9]

Arulampalam et al. (2000) analyse Markovian unemployment persistence in the UK using Waves 1 to 5 of the British Household Panel Survey (BHPS). Focusing on the respondents’ labour market status measured at each consecutive interview, the authors find evidence in support of the “scarring” hypothesis, in particular for mature workers. Stewart (2007) models jointly persistence in low pay and persistence in unemployment, analysing their interrelations.

[9] For more US based literature see, among others, Mroz and Savage (2006). Using data from the 1979 National Longitudinal Survey of Youth (NLSY79), the authors find evidence of short term persistence of unemployment for young people, while persistence tends to disappear in the long term.

Both low pay jobs and unemployment spells are in fact likely to negatively influence human capital accumulation and to provide adverse signals to potential employers. Using data from the BHPS for the years 1991-1996, the author shows that past low-wage employment is as important as past unemployment in reducing the probability of being employed at a given point in time. Moreover, the analysis provides evidence in support of a 'no pay-low pay' cycle as those entering low-wage employment after a spell of unemployment are significantly more likely to re-enter unemployment than those entering in a higher paid employment after the unemployment spell. Consistent evidence also emerges from Böheim and Taylor (2002).

Evidence on the longer term scarring effect of unemployment can be found in, among others, Gregg (2001) and Burgess et al. (2003).[10] Gregg (2001) uses the National Child Development Study (NCDS) to measure the impact of unemployment experiences before the age of 23 on the probability of experiencing unemployment or inactivity between the ages of 28 and 33. The author provides evidence in favour of a significant scarring effect from youth unemployment, in particular for males. Burgess et al. (2003) use data from six waves of the Labour Force Survey between 1981 and 1996 to perform a pseudo-cohort analysis of the impact of the early career unemployment rate on future employment prospects. The authors find evidence of scarring only for the less skilled, while the more skilled seem to benefit from early career unemployment rates.[11] Unemployment experiences are also shown to have a negative and long lasting impact on

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[10] See also Kalwij (2004). Using UK administrative data, the author shows that a quarter of the sample of young men used in the analysis is not able to find stable employment by age 35, while this is the case for the rest of the sample. Those failing to enter into stable employment are mainly low-skilled individuals, and results suggest the presence of structural employment instability for this group.

[11] See Eliason and Storrie (2006) and Nordström Skan (2004) for studies using Swedish administrative data. Eliason and Storrie (2006) analyse the impact of unemployment on wages and employment patterns for a sample of workers from plants which shut down in 1987 and 1988. The authors find evidence of a recovery both in terms of wages and employment in the years immediately following the plant dismissal. However, convergence stops at the onset of the 1991 recession and a divergence trend occurs until 1993. The authors show that dismissed workers still suffer a penalty both in terms of unemployment incidence and wages 12 years later. They conclude that workers who experience unemployment are also more sensitive to the macroeconomic climate. Nordström Skan (2004) finds evidence of a long-term scarring effect from unemployment, exploiting the between-sibling variation to control for unobserved heterogeneity.

outcomes such as salaries (Gregory and Jukes, 2001; Arulampalam, 2001; Mroz and Savage, 2006; Eliason and Storrie, 2006) and wellbeing (Bell and Blanchflower, 2011a, b; Clark et al., 2001).

This work contributes to the rich literature on unemployment persistence in two ways. First, it addresses the extent to which unemployment experiences have scarred British workers during the Great Recession by analysing persistence in unemployment incidence between 2007 and 2011. Second, the paper provides an insight on the dynamics of "true state dependence" over the business cycle by analysing the extent to which the scarring effect varies with local labour market conditions and by comparing estimates relative to the last recession with that of a period of falling unemployment, the early '90s, and a period of relative stability in terms of unemployment rates such as the early 2000s (Figure 2.1).

The sign of the association between true state dependence and business cycle cannot, in fact, be determined *a priori*, as it is closely related to the nature of the causes of unemployment scarring. Kroft et al. (2013) summarise four possibilities.[12] First, models focusing on human capital depreciation (Pissarides, 1992; Acemoglu, 1995; Edin and Gustavsson, 2008) predict that true state dependence should be independent from labour market conditions as skill depreciation is assumed not to be affected by unemployment levels in the economy. Second, models focusing on search behaviour predict that discouragement, and hence a fall in search intensity, will occur when employment perspectives deteriorate, with a consequent positive relationship between scarring effect and unemployment cycle (e.g., Ayllón, 2013).Third, models which identify in the negative signalling of unemployment the main source of state dependence predict for unemployment to be less scarring in times of adverse labour market conditions, on the grounds that unemployment experiences are less informative about the unobserved characteristics of job

[12] Although the authors focus on the relationship between duration dependence and labour market conditions, the theoretical predictions are largely applicable to the case of state dependence in unemployment persistence.

applicants in periods of slack labour markets (Lockwood, 1991). Among others, Biewen and Steffes (2010) find supporting evidence analysing unemployment persistence in Germany, while Kroft et al. (2013) and Omori (1997) provide evidence for the US, with a focus respectively on duration dependence and lagged duration dependence.

Fourth, a number of models focus on crowding in labour markets. Among them, Blanchard and Diamond (1994) predict that if the length of the current unemployment spell provides a negative signal to potential employers in the hiring process, then high levels of unemployment are expected to reduce the probability of finding a job as it is more likely that some other worker with a shorter spell of unemployment will apply. Michaillat (2012) proposes a search and matching model in which unemployment due to jobs rationing is likely to arise even in the absence of frictional unemployment. The author shows that rationing unemployment (i.e., unemployment due to a shortage of jobs) quantitatively outweighs frictional unemployment in times of slack labour markets, while the opposite is true in times of favourable labour market conditions. In both cases, the theoretical predictions are that scarring will be worse during adverse labour market conditions because of crowding. Evidence in support of job rationing and crowding in the labour market can be found in Crépon et al. (2013). Analysing the impact of a randomised labour market programme aimed at providing job placement assistance to skilled unemployed individuals in France, the authors find that the employability of non-treated workers is significantly worsened by the programme, especially in times of adverse labour market conditions. The authors identify in job rationing and crowding in the labour market the main source of this negative externality.

Our analysis shows strong evidence in support of the presence of true state dependence during the Great Recession and, consistent with the crowding and job rationing models, it provides an indication of a negative relation between true state dependence and business cycle, both within and between the three time periods analysed. Policy interventions aimed at reducing unemployment are, therefore, likely to have positive longer term effects on the unemployment risk, in particular during downturns. Our estimates are based on random effect dynamic probit models with Wooldridge's (2005) solution for the initial condition problem and they make use of data from both the British Household Panel Survey (BHPS) and Understanding Society.[13]

The paper is organised as follows: Section 2.2 introduces the data and the methods used for the analysis; results are presented and commented in Section 2.3; conclusions follow in Section 2.4.

2.2 Data and methods

2.2.1 Data and descriptive statistics

Unobserved heterogeneity is a potential source of bias for estimates of true state dependence. To correctly disentangle the effect of unobserved individual characteristics, i.e. the individual propensity to be unemployed, from that of past unemployment incidence is a major identification challenge and panel data are powerful tools in achieving consistent estimates of the parameters of interest. For this reason, we make use of two rich sources of panel data collecting detailed information on household and individual circumstances during the last two decades: the British Household Panel Survey (BHPS) and Understanding Society.[14]

In addition to their panel dimensions, the BHPS and Understanding Society surveys are well suited for our analysis for at least two reasons. First, the surveys collect a rich set of information which allows to control for the main determinants of unemployment risk. The reminder of the section describes them in details. Second, the length of the time period covered, and the across-time consistency in the definitions of the variables used in the analysis, allows us to investigate

[13] The analysis relative to the early '90s is closely related to Arulampalam et al. (2000). See Gregg and Wadsworth (2010) for an analysis of unemployment during the last two decades.
[14] University of Essex, Institute for Social and Economic Research (2010b); University of Essex, Institute for Social and Economic Research, NatCen Social Research (2014a); see Taylor et al. (2010) and <https://www.understandingsociety.ac.uk> for info on the British Household Panel Survey and Understanding Society, respectively.

the existence of heterogeneity in true state dependence across different phases of the business cycle.

The British Household Panel Survey started in autumn 1991 and ran for 18 annual waves. Interviews usually took place during autumn or winter and respondents were typically re-interviewed in the same period each year. After Wave 18, BHPS respondents were reabsorbed into Understanding Society, a larger household survey lunched in 2009, and were re-interviewed in 2010/11 and 2011/12. Since we only use Understanding Society to follow former BHPS respondents, we refer to 2010/11 and 2011/12 data as Wave 19 and Wave 20, respectively. In our analysis we use data from three non-overlapping sub-periods: we analyse data from Waves 16, starting in autumn 2006, to 20, to estimate true state dependence during the Great Recession; Waves 9-13, covering the period from autumn 1999 to winter 2004, are used to evaluate the scarring effect of unemployment in a period of low and stable unemployment (see Figure 2.1); similar to Arulampalam et al. (2000), Waves 1-5 are used to study the persistence in unemployment incidence during a period of high but declining unemployment.

As well as the original BHPS sample, various subsamples took part in the BHPS over time. In particular, a sample of respondents to the European Community Household Panel Survey (ECHP) was part of the study between Waves 7 and 11; the Wales and Scotland boost samples were included in Wave 9, and a Northern Ireland sample in Wave 11. With the aim of maximising the sample size, our study makes use of the original BHPS sample, present in all the sub-periods used, and the boost samples for Scotland and Wales, present in Waves 9-13 and Waves 16-20 but not in Waves 1-5. We did not include the ECHP subsample because it is not continuously present in any of the sub-periods used. Nor did we use the Northern Ireland subsample because it would be only part of the analysis related to Waves 16-20.

At the beginning of each of three sub-periods analysed, i.e., Waves 1, 9 and 16, we keep full respondent males, aged between 16 and 50, who are not in full-time education and are active in the labour market, i.e., either working or in unemployment. With respect to people in work, we classify as labour market active both employees and self-employed individuals who declared that they did paid work in the week before the interview or had a job which they were away from. We define as unemployed those respondents who were not in work and reported that they had looked for a job in the last 4 weeks. The rest are classified as inactive and, hence, not included in our estimation sample. It should be noted that the unemployed definition used in our analysis is consistent with the one of Arulampalam et al. (2000) and Stewart (2007), although an additional condition of immediate availability to start working is required in these papers. As a robustness check, we repeat the analysis with a less stringent definition of unemployment which includes also those defining themselves as unemployed even if the job search criteria are not met. Each respondent stays in our estimation sample until a full interview is missed, or the person becomes inactive, enters full-time education, or has a missing value in any of the other variables used in the analysis. Hence, our final sample is an unbalanced panel with complete information on the respondents until the end of the sub-period analysed or until the respondent is excluded. A sample of this sort can be defined as “compact” but unbalanced.

Tables 2.1 to 2.3 report descriptive statistics for each of the sub-periods analysed. As shown by Table 2.1, the proportion of unemployed continuously falls between Wave 1 and Wave 5, being close to 10 percent and just below 4 percent in Wave 5. The average proportion over the period is 7 percent. The probability of being unemployed at a given point in time conditional on being unemployed in the previous wave is above 56 percent, while 2.8 percent of those employed in the previous wave are observed to be unemployed at the time of interview. These raw data estimates are in line with those reported by Arulampalam et al. (2000), and support the existence of persistence in unemployment incidence.

The majority of the UK based literature finds a positive effect of the local unemployment to vacancy ratio on the probability of being unemployed at a given point in time (e.g. Arulampalam et al., 2000, Arulampalam and Stewart, 2009) and Biewen and Steffes (2010) find evidence that the scarring effect is negatively related to the unemployment cycle in Germany. We control for local labour market conditions through the claimant proportion, a measure of the proportion of claimants of unemployment related benefits over the population aged 16-64 at the local authority district level.[15] Consistent with the trend of the unemployment rate reported in Figure 2.1, the claimant proportion increases between Wave 1 and Wave 2, and starts to decrease in later waves.

A higher incidence of full-time education among youths, as well as ageing and the fact that we do not allow new entries into our estimation sample, explains the lower and declining-over-time proportion of youths aged between 16 and 25 compared with other age groups. Arulampalam et al. (2000) show that youths have been less affected than adults by scarring in the early '90s; we test whether a similar pattern emerges during the Great Recession.

On aggregate, the majority of respondents in our sample are above CSE education level, and 22.8 percent report no qualifications among those listed. Following Arulampalam and Stewart (2009), the education variable is considered time invariant and measured at the beginning of the sub-period because, a) observations drop from our estimation sample as soon as they are observed in full-time education; and b) few changes in qualifications occur. The great majority of respondents in our sample are home owners, with a prevalence of social renters over private renters among non-home owners. The proportion of married people increases over time while the average number of children in the household ranges between 0.89 and 0.85 in the period analysed. Only 3 percent of respondents report to be in poor health while 3 percent are ethnically non-white.

[15] See NOMIS website for more information. Data downloaded in December 2014.

Table 2.2 reports descriptive statistics for Waves 9 to 13. On average, 3.5 percent of the sample is observed to be in unemployment at the time of the survey and the proportion is declining over time. Evidence of persistence in unemployment incidence in the raw data emerges as the probability of being in unemployment conditional on being unemployed in the previous wave is about 45 percent. This represents a considerably higher value than the 1.6 percent probability faced by those employed in the previous wave. It should be noted that the claimant proportion shows a slowly declining trend across waves, consistent with the broadly stable unemployment rate in the same period. The use of a boost sample for Scotland and Wales explains the high proportion of people living in these two regions.[16]

With respect to Waves 16-20, the number of observations is declining over time as expected. However, a significant drop occurs between Wave 18, the last wave of the BHPS, and Wave 19, the first wave in which former BHPS respondents were interviewed as part of Understanding Society. Table 2.3 shows that the proportion of unemployed declines between Wave 16 and Wave 18, reaching a minimum of 2.1 percent in Wave 18, i.e., during late 2008 and early 2009, and it rises considerably in Wave 19; the aggregate proportion of unemployed is approximately 3 percent.[17] On aggregate, the probability of being in unemployment at a given point, conditional on being unemployed in the previous wave, is close to 41 percent. The same probability amounts to 1.5 percent for those who were previously employed. Consistent with previous literature, this evidence confirms the existence of persistence in unemployment incidence in the raw data.

[16] The item measuring general heath is different in Waves 9, 19 and 20 compared with the other BHPS waves. Categories have been re-grouped in order to be as comparable as possible, but this is likely to explain the drop in the proportion of people in bad health that occurs in these waves.

[17] A considerable drop in the proportion of unemployed occurs between Waves 1 and 2, 9 and 10, and 16 and 17. As well as a decline in the aggregate unemployment rate, also confirmed by Figure 1, the drop is likely to be caused to a certain extent by the way our sample is built, as incidences of inactivity and missing interviews seem to affect more the unemployed than the employed. Although endogenous selection into economic activity could be an issue, in their study on low-pay persistence Cappellari and Jenkins (2008) show that ignoring endogenous selection into employment does not introduce sizeable bias into estimates of covariate effects. Moreover, the robustness check in which we estimate our models by also defining as unemployed those inactive respondents who defined themselves as unemployed confirms our findings.

Comparing the descriptive statistics across sub-periods, it should be noted that, i) the levels of the claimant proportion are considerably higher in this first sub-period than they are during the Great Recession; ii) the age profile varies across sub-periods, with a higher proportion of youths and a lower proportion of adults in the early ‘90s, arguably because of the subsequent expansion in access to further education; and iii) the level of academic qualification is substantially lower in the Wave 1 to 5 sub-period, with 12.7 percent of respondents with a degree or more, and over 22 percent of individuals having no qualifications. A further improvement in the education profile of respondents also arises when statistics relative to the Great Recession sub-period are compared to those relative to Waves 9-13.

Descriptive statistics show the presence of persistence in unemployment incidence in all the sub-samples used. However, controlling for observable and unobservable characteristics is necessary to assess the existence of true state dependence in the data. With respect to observables, for example, Tables 2.1-2.3 show a high degree of heterogeneity in characteristics of the respondents in the three sub-samples, with people who are in the “Great Recession sample” usually older and more educated than those in the early ‘90s sample. Similar considerations apply to the claimant proportion. The next sub-section introduces the identification strategy that we use to disentangle the effect of previous unemployment from those of observed and unobserved characteristics, and to estimate true state dependence.

2.2.2 Methods

Similarly to numerous previous works on persistence in unemployment incidence, we use a dynamic random effect probit to identify the presence of true state dependence in our data (Arulampalam et al., 2000; Biewen and Steffes, 2010; Stewart, 2007) and we adopt the Wooldridge (2005) solution for the initial conditions problem. See Arulampalam and Stewart

(2009) for an exhaustive description of the three most commonly used methods to deal with the initial condition problem, i.e., Heckman (1981a,b), Orme (1997; 2001) and Wooldridge (2005).

An individual i at time of interview t is observed to be in unemployment if her unobserved propensity to be unemployed U_{it}^{*} crosses a threshold of 0. The propensity to be unemployed is assumed to be a function of unemployment status at the time of the previous interview, U_{it-1}, a row vector of observable characteristics, $\boldsymbol{X}_{it}$, an individual specific unobserved effect c_i and a random error term e_{it}.

$$U_{it}^{*} = \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + c_i + e_{it}\,, \qquad i = 1, \dots, n \text{ and } t = 2, \dots, T_i \tag{1}$$

with $e_{it} \sim N(0,1)$. Following Mundlak (1978) and Chamberlain (1984), we allow for correlation between the unobserved heterogeneity term c_i and observed characteristics $\boldsymbol{X}_{it}$ by assuming a relationship of the form $c_i = \overline{\boldsymbol{X}}_i\boldsymbol{\theta} + \alpha_i$, where $\alpha_i \sim iid\ N(0, \sigma_a^2)$ and independent of $\boldsymbol{X}_{it}$ and e_{it} for all i and t (Stewart, 2007; Arulampalam et al., 2000). We are thus left with an equation of the form:

$$U_{it}^{*} = \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + \alpha_i + \overline{\boldsymbol{X}}_i\boldsymbol{\theta} + e_{it}\,, \qquad i = 1, \dots, n \text{ and } t = 2, \dots, T_i \tag{2}$$

The model in Equation (2) can be consistently estimated only if the initial condition U_{i1} is exogenous. This would be the case, for example, if we had observed individuals since the beginning of the data generating process. In the presence of a correlation between initial condition and unobserved heterogeneity, however, the estimate of the parameter of interest γ would be biased upward because part of the effect of the unobserved heterogeneity would be captured by the coefficient on the lag dependent variable (Stewart, 2007).

Following Wooldridge (2005), the problem of the initial condition is addressed in the spirit of Mundlak (1978) and Chamberlain (1984) by controlling for a linear relationship between unobserved heterogeneity and initial condition and estimating the model conditional on the initial value of the variable of interest. In particular, it is assumed that:

$$\alpha_i = a_0 + a_1 U_{i1} + \varphi_i \tag{3}$$

where $\varphi_i \sim iid\ N(0, \sigma_\varphi^2)$. Substituting (3) into (2)

$$U_{it}^* = \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + a_0 + a_1 U_{i1} + \varphi_i + \overline{\boldsymbol{X}}_i\boldsymbol{\theta} + e_{it} \quad i = 1, \dots, n \text{ and } t = 2, \dots, T_i \tag{4}$$

Equation (4) can be easily estimated using a random effect probit.

The coefficient on the lagged unemployment status is our coefficient of interest. A positive and significant coefficient implies the presence of true state dependence since, controlling for observed characteristics and unobserved heterogeneity, past unemployment influences current unemployment status. Consistent with other studies on unemployment persistence, the vector $\boldsymbol{X}_{it}$ contains variables such as age, highest academic qualification, marital status, general health, proportion of unemployment benefits claimants in the population aged 16-64 at the local authority district level, region of residence, and wave dummies. $\overline{\boldsymbol{X}}_{it}$ contains the within-individual average of time-varying covariates. Due to lack of variation in regional mobility, averages of region dummies are not included in the model. The variable age is assumed to be exogenous to the unobserved heterogeneity term, so average age is, similarly, not included.

Following Wooldridge (2005, 2008), average partial affects (APE) are based on

$$\mathrm{E}[\Phi(\boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + a_0 + a_1 U_{i1} + \varphi_i + \overline{\boldsymbol{X}}_i\boldsymbol{\theta})] \tag{5}$$

where the expectation is over the distribution of $(U_{i1}, \overline{\boldsymbol{X}}_i, \varphi_i)$

$$APE = \frac{1}{N}\sum_{t=2}^{T_i}\sum_{i=1}^{n}\left\{\Phi\left(\frac{\boldsymbol{X}_{it}\widehat{\boldsymbol{\beta}} + \hat{\gamma}+\hat{a}_0+\hat{a}_1 U_{i1} + \overline{\boldsymbol{X}}_i\widehat{\boldsymbol{\theta}}}{\sqrt{\left(1+\hat{\sigma}_{\varphi}^2\right)}}\right) - \Phi\left(\frac{\boldsymbol{X}_{it}\widehat{\boldsymbol{\beta}} + \hat{a}_0 + \hat{a}_1 U_{i1} + \overline{\boldsymbol{X}}_i\widehat{\boldsymbol{\theta}}}{\sqrt{\left(1+\hat{\sigma}_{\varphi}^2\right)}}\right)\right\} \tag{6}$$

where N identifies the total number of individual-time observations in our sample. In order to evaluate the extent to which true state dependence varies within the three sub-periods analysed, we also compute wave specific APEs by averaging over the wave specific population. We follow the same strategy for the calculation of APEs by age and by level of local unemployment. Standard errors are computed through bootstrapping with replacement with 500 replications.

In the spirit of Biewen and Steffes (2010) and Arulampalam et al., (2000), respectively, we also investigate whether true state dependence varies with age and levels of local unemployment. Since our model is non-linear, our base specification presented in equation (4) already allows the average partial effects on the lagged unemployment status to vary with the characteristics of the respondent. In this context, even if the inclusion of an interaction term allows more flexibility in analysing the relationship between true state dependence and individual characteristics, a lack of significance in the interaction term does not necessarily imply a zero gradient in true state dependence with respect to changes in such characteristics. Hence, when we analyse whether true state dependence varies between claimant proportion or age of the respondent, we act according to the following strategy. First, we augment our base specification by including an interaction term between the lagged unemployment status and the claimant proportion (Model 3) or age (Model 4). In Model 3 we also we include an interaction term between the unemployment status at first interview and the claimant proportion. If these interaction terms are statistically significant, then we compute APEs using the model including the interactions. Otherwise we compute APEs from Model 2 in order to maximise statistical efficiency. [18]

2.3 Results

In this section we present the results of our analysis. For each sub-period we estimate 4 different models. Model 1 is a pooled probit, which allows us to analyse the relationship between lagged and current unemployment status controlling for the observable characteristics of the respondents, but not for the unobservable ones. Model 2, which consists of a dynamic random effect probit with Wooldridge's (2005) solution for the initial condition problem, is our baseline specification as it also allows us to control for unobserved time invariant characteristics of the individual. In Model 3 we extend our baseline specification by controlling for the interaction between lagged unemployment status and claimant proportion. The aim of this specification is to allow more flexibility in analysing possible relations between local labour market conditions and true state dependence (Biewen and Steffes, 2010). In Model 4 we add an interaction term between our lagged unemployment status and age of the respondent. Arulampalam et al. (2000) show that youths below 25 years old are less scarred by unemployment than adults during the early '90s, and we check if the finding is still valid during the early 2000s and the Great Recession.

After analysing the three sub-periods on their own in subsections 1 to 3, we also report estimates of true state dependence for a hypothetical individual with fixed characteristics in each of the three sub-periods analysed. This exercise allows us to study the patterns of the scarring effect of unemployment across the three sub-periods analysed, holding constant the observable characteristics of the individual. The last subsection discusses a number of robustness checks.

[18] We also estimate a model including an interaction term between lagged unemployment status and wave dummies. We do not report estimates from this specification because interaction terms are never statistically significant.

2.3.1 The early ’90s

In this section we focus our analysis on the period ranging from 1991 to 1995, a period of declining unemployment after the early ’90s recession. We partly replicate Arulampalam et al. (2000), although we use slightly different regressors and a different solution to the initial condition problem to obtain estimates of state dependence that are consistent across the three sub-periods used. Our coefficient estimates are reported in Table 2.4, and APEs in Table 2.5.

Consistent with previous research, the pooled probit estimates (Model 1) show a positive relationship between lagged and current unemployment status. This result implies that, controlling for a number of observed characteristics, those unemployed in the previous wave face a higher risk of current unemployment than those previously employed. However, since Model 1 does not control for individual unobserved heterogeneity, the finding is not to be interpreted as evidence of true state dependence. Among other regressors, estimates from Model 1 show that the claimant proportion is positively associated with unemployment probability, while the sign of the association is negative for age and education, with older and more educated respondents less likely to experience unemployment at a given point in time. Estimated coefficients also show that, compared to private renters, home owners face a lower unemployment risk while social renters are more likely to be in unemployment. Finally, being married is associated with a lower unemployment probability, while number of children in the household is positively associated with unemployment risk. Among wave dummies, only the coefficient on Wave 5, correspondent to year 1995/96, is statistically significant.

Average partial effects from Model 1 are reported in Table 2.5. Results show that after controlling for the observable characteristics of the respondent the average partial effect on the lagged unemployment status is close to 0.4, meaning that, on average, a person who was unemployed last year is 40 percentage points more likely to be unemployed this year than a similar person who was employed last year.

Estimates from Model 2 are based on a random effect dynamic probit with Wooldridge's (2005) solution to the initial condition problem. Model 2 represents our preferred specification as it controls both for the effect of observed characteristics as well as unobserved time invariant characteristics. Consistent with previous literature (e.g., Arulampalam et al., 2000; Stewart, 2007), the coefficient on the lagged unemployment status is positive and statistically significant. The result is consistent with the existence of true state dependence as past unemployment incidence significantly affects current unemployment probability. In particular, the APE of lagged unemployment is approximately 8.4 percentage points, while wave specific true state dependence is estimated to decline over time from about 10 percentage points in Wave 2 to 6.2 percentage points in Wave 5. As expected, estimates of true state dependence from Model 2, which controls for individual unobserved heterogeneity, are considerably smaller than those from Model 1, and even smaller than raw data state dependence.

With respect to other regressors, estimated coefficients confirm the importance of age and education in affecting unemployment risk. Also, the claimant proportion has a positive and significant coefficient, confirming that adverse labour market conditions increase the probability of being unemployed.

APEs from Model 2 show a declining trend over time, a pattern similar to that followed by unemployment rate in the same period (Figure 2.1). With the aim of analysing the relationship between state dependence and labour market conditions, we include an interaction term between lagged unemployment status and claimant proportion (Model 3). Estimates show that the interaction term is not statistically significant. In a different specification (not reported) we interacted the cyclical component of claimant proportion in the spirit of Biewen and Steffes

(2010), but without finding any significant effect. APEs on lagged unemployment after Model 3, reported in Table 2.5, are consistent with those computed after our base specification and confirm the declining trend in true state dependence over time.

As the interaction term between unemployment status at previous interview and claimant proportion is not statistically significant, for greater statistical efficiency we use estimates from Model 2 to evaluate to what extent the scarring effect of unemployment varies among individuals experiencing different labour market conditions. Thus, we evaluate average partial effects on lagged unemployment over the distribution of claimant proportion discretised in 2 percentage point bands. Estimates reported in Table 2.6 show that those experiencing higher levels of local unemployment are more scarred by unemployment experiences. A t-test confirms that the scarring effect at each subsequent band of claimant proportion is statistically different from the one faced by individuals living in areas where the proportion of active population claiming unemployment related benefits ranges between 2 and 4 percentage points. Unlike the results presented by Biewen and Steffes (2010) for Germany, our findings suggest for state dependence to be higher in periods or areas of high unemployment and hence to be negatively correlated with the business cycle.

Consistent with Arulampalam et al. (2000), the coefficients from Model 4 show that youths below the age of 26 are less affected by the scarring effect than other age groups. Arulampalam et al. (2000) impute this result to job shopping, i.e., a propensity to change job several times during the youth period. APEs after Model 4, reported in Table 2.5, are consistent with the findings of our base specification. APEs averaged across age groups after both Models 2 and 4 are reported in Table 2.7. Following our base specification, youths are the most scarred by unemployment experiences, while estimates of true state dependence for older workers are between 7.1 and 7.9 percentage points. APEs based on Model 4, which allows more flexibility in the relationship between age and the scarring effect of unemployment, show that youths are less scarred by unemployment experiences than mature workers, although the differences are not statistically significant. Despite the interaction terms between unemployment status at previous wave and age bands are statistically significant, their introduction makes the estimates of APEs over age groups less precise.

Our analysis hence strongly supports the existence of true state dependence in a period ranging from 1991 to 1995/96. Over the analysed period, the estimated average partial effect following our base model specification is close to 8.5 percentage points with a declining trend from about 10 percentage points in Wave 2 to 6.2 percentage points in Wave 5. Our estimates show a counter-cyclical pattern of true state dependence as unemployment is less scarring if local labour market conditions are more favourable.

The results are consistent with several UK-focused works based on early ’90 data, although the size of our estimates of true state dependence is smaller. In particular, using BHPS data covering 1991-1995, Arulampalam et al. (2000) report APEs which decline from 11.7 to 7.9 percentage points for youths aged under-25 and from 22.6 percent to 13.9 percent for adult aged 25 or older. Using 1991-1996 BHPS data, Stewart (2007) estimate a true state dependence parameter of 15 percentage points in the closest model specification to the one used in this work. The differences in the sizes of the estimated effects are likely to be due to differences in the model specification, in the variables definition and in methodology adopted to overcome the initial condition problem.

In the following subsections we perform our estimations on two different sub-periods, the early 2000’s and the Great Recession. As well as providing consistent estimates of true state dependence in those periods, the analysis will contribute to a better understanding of its relationship with the business cycle.

2.3.2 The early 2000s

This section analyses state dependence in unemployment incidence in the early 2000s. As shown in Figure 2.1, between 1999 and 2003 unemployment was low and broadly stable. The macroeconomic scenario in this period is, therefore, radically different both from the one analysed above, characterised by declining unemployment rates, and from the one studied in the next subsection, characterised by a considerable increase in unemployment during the Great Recession. Model specifications are the same as in the previous section: Model 1 contains a pooled probit analysis; in Model 2 we estimate the dynamic random effect probit model with the Wooldridge (2005) solution for the initial condition problem; in Models 3 and 4, we modify our base specification by introducing interaction terms between the lagged unemployment status and, respectively, claimant proportion and age categories.

Comparing the estimated coefficients, reported in Table 2.8, with those relative to the analysis of Waves 1-5, three main differences arise: i) a negative but not significant effect of claimant proportion on the probability of being unemployed in model specifications 2-4; ii) in all the model specifications the “none of these” education category becomes the only one with a statistically positive coefficient; iii) in Model 4, the coefficient on the interaction term between lagged unemployment status and age categories becomes not statistically significant with the exception of the 46-55 age category that is just on the margin of statistical significance.

Focusing on the APEs reported in Table 2.9, for Model 1 we estimate an effect of 0.27 overall, with an irregular pattern between waves. According to APEs after Model 2, those previously unemployed have, on average, a 6 percentage points higher probability of being currently unemployed than those previously in employment. Despite being irregular, no particular pattern can be identified between waves. APEs from Models 3 and 4 show consistent results. In Table 2.10 we report APEs after model (2) evaluated over the discretised distribution of claimant proportion. Estimates confirm that workers experiencing worse labour market conditions are more scarred than those experiencing lower levels of local unemployment.[19]

Table 2.11 reports APEs by age group estimated after Model 2, showing that youths suffer the most from past unemployment experiences. Since the interaction term between lagged unemployment and age dummy is just at the margin of statistical significance in Model 4, we also report APEs by age group computed after Model 4. The results, reported in the second panel of Table 2.11, show a U-shaped trend of true state dependence with respect to age, although the lack of statistical significance of the interaction terms makes our APEs for the youngest population group not statistically different compared to those of older groups.

Our analysis therefore shows the presence of true state dependence during the early 2000s, and its average over the time periods is smaller than the one estimated for the early ’90s. In Waves 9-13, estimates of true state dependence show a slightly irregular but overall constant pattern and support a negative relationship between the business cycle and the scarring effect of unemployment.

2.3.3 The Great Recession

Table 2.12 reports the estimates of Models 1-4 for Waves 16-20, i.e., the sub-period of the Great Recession. Consistent with findings relative to the other sub-periods analysed, the coefficient on the lagged unemployment estimated by the pooled probit (Model 1) is positive and statistically

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[19] As a robustness check, we also computed APEs on lagged unemployment status by fixing the values of claimant proportion at various increasing values. This method of computing APEs imposes to all the individuals in our sample to experience the same level of claimant proportion, leaving all the other variables at individual values. While we find consistent results with respect to the early ’90s and Great Recession sub-periods, i.e. APE increases with level of claimant proportion, this is not the case for the early 2000s sub-period. The result is arguably driven by the lack of precision with which the coefficients on the claimant proportion and on the average over time of the claimant proportion faced by the individual are estimated. Excluding the average over time of time varying covariates, which are jointly not statistically significant, produce consistent results with those presented in the main sections of the paper, and confirms a positive association between claimant proportion and scarring effect both averaging over the population of people experiencing different levels of unemployment and by exogenously fixing claimant proportion at different values of interest.

significant. Unlike the early ’90s sub-period, local labour market conditions seem not to significantly influence the unemployment risk as the coefficient on the claimant proportion is positive but not statistically significant. The lack of an effect can, however, be explained by a high degree of correlation between wave dummies and claimant ratio. Indeed, in all model specifications the exclusion of wave dummies from our estimated equation leads to larger in size and statistically significant coefficients on the claimant ratio. Among other regressors, estimates from Model 1 confirm both the negative association between age and unemployment risk found for the previous sub-periods and, similar to the Wave 9 to 13 sub-period, also the role played by lack of educational qualifications in increasing the unemployment probability. APEs after our pooled probit specification (Model 1), reported in Table 2.13, show that the effect on the lagged unemployment status is close to 0.2. Wave specific APEs show the presence of a shift in Wave 19 and Wave 20.

Model 2, which allows us to control for unobserved heterogeneity as well as the observed characteristics of the individual, provides evidence in support of the existence of true state dependence during the Great Recession. The coefficient on lagged unemployment is, in fact, positive and statistically significant, while APEs (Table 2.13) show that those who were unemployed at a given wave experience a probability of being in unemployment at the following wave that is 7.9 percentage points higher than for those who were previously employed. The scarring effect of unemployment shows an increasing pattern by wave, as our estimates are close to 7 percentage points in 2007/08 and 2008/09 and peak at 9.9 and 8.4 percentage points in Waves 2010 and 2011, respectively. Among other regressors, the coefficient on the local claimant proportion is not statistically significant, arguably for collinearity with the wave dummies, while age, having no academic qualifications and the dummy relative to Wave 19 significantly affect the unemployment risk.

In Models 3 and 4 we fail to find any significant interaction term between lagged unemployment status and, respectively, claimant proportion (Model 3) and age (Model 4). APEs relative to these specifications confirm the findings from Model 2. As for the previous sub-periods, we report in Tables 2.14 and 2.15, respectively, APEs by claimant proportions and by age after Model 2. The estimates confirm the positive association between local unemployment and state dependence, as the APE on lagged unemployment is significantly higher for those experiencing a high level of claimant proportion when compared with those experiencing tighter labour market conditions. Consistent with APEs following our base specification for the other sub-periods, the estimated APEs show a decreasing pattern in scarring by age group, with youths more affected by unemployment experiences than adults.

Our analysis thus confirms that unemployment is also a scarring experience during the Great Recession. Moreover, our results suggest the existence of a negative association between business cycle and true state dependence in the years of the Great Recession as well as in the other sub-samples.

Hence, comparing across sub-periods, our results show that: i) unemployment experiences have had a scarring effect on future employability in the last two decades; ii) workers experiencing worse local labour market conditions are significantly more scarred than those experiencing tighter labour markets; and iii) youths are those more at risk of being scarred by unemployment experiences, although allowing more flexibility in the relationship between unemployment status in previous wave and age shows that older workers have been scarred at least as much as youths in the early ’90s.

Figure 2.2 reports our wave specific estimates of true state dependence after Model 2 for the three sub-periods analysed together with trends for male annual unemployment rates in Great Britain as reported in Figure 2.1. Similarly, Figure 2.3 provides a scatterplot of our estimates for unemployment scarring and male unemployment rates. Point estimates are weighted by the inverse of their estimated variance. The plots provide descriptive evidence that the negative association between scarring effect of unemployment and business cycle holds not only within but also between sub-periods. If confirmed by future research, such results will be consistent with factors such as crowding in the labour markets (Michaillat, 2012; Blanchard and Diamond, 1994) at least compensating the beneficial effect of the reduction in the stigma associated with unemployment during recessions.[20]

In the next subsection we further develop the role of the business cycle in affecting unemployment experience by analysing the scarring effect of unemployment for a hypothetical person with fixed characteristics across the three sub-periods.

2.3.4 Cross period analysis

Previous sections have provided evidence in favour of true state dependence in the three sub-periods analysed and have provided evidence supporting that unemployment scarring is basically counter-cyclical, as a positive association between true state dependence and unemployment cycle arises.

In this subsection we report the estimates of true state dependence after Model 2 for a reference person across the three sub-periods. The reference person has the following characteristics: aged between 16 and 25 years; 'O' Level education; home owner; not married and with no children; not in poor health; from a white ethnic background; and living in the Midlands. Claimant proportion is fixed at the wave-specific average faced by people living in the Midlands. The exercise allows us to better appreciate the extent to which scarring effect has changed in the past

[20]While our estimates of true state dependence are wave specific, annual unemployment rates refers to calendar years. We matched the two measures by using the year in which wave-specific interviews officially started to take place (e.g., 1992 for Wave 2, etc.). This explains the missing estimate of true state dependence in Figure 2 for the year 2010, as we assigned the value of true state dependence relative to Wave 18 to the year 2008 and those relative to Wave 19 to the year 2010.

two decades by holding constant the observed characteristics of the individual. As far as unobserved heterogeneity and initial conditions are concerned, following Wooldridge (2005) we use the observation specific values.

Tables 2.16-2.18 report APEs for the reference person across the three sub-periods analysed. Compared to Tables 2.5, 2.9 and 2.13, the estimates show that the APEs for the reference person are usually bigger and less precise than the APEs calculated for the sub-period populations. The results confirm the main findings of our analysis: evidence of true state dependence arises from the whole period analysed, despite being just at the margin of statistical significance for the Wave 9-13 sub-period. Furthermore, its magnitude is negatively correlated with the business cycle as wave specific APEs follow a decreasing pattern during the first sub-period, are stable during the late ’90s, and increase during the Great Recession.

2.3.5 Robustness checks

We perform a number of robustness checks. First, given that discouraged unemployed who do not meet the job search criterion would be classified as inactive and, hence, excluded from our estimation sample, we repeat the analysis using an alternative definition of unemployment which relaxes the job search criterion and classifies as unemployed all those who are not employed or self-employed and who classify themselves as unemployed.[21] The results, reported in Column 1 of Appendix Tables 2.A1, 2.A3 and 2.A5, show evidence of state dependence for all the periods analysed. APEs, reported in Column 1 of Tables 2.A2, 2.A4 and 2.A6, confirm that the scarring effect is negatively correlated with the business cycle. We also find evidence in support of true state dependence being present in all the sub-periods analysed, and of a pattern over time which is consistent with scarring effect being negatively correlated with the business cycle, when we

[21] See Arulampalam (2002) for a discussion on the implications of using different definitions of unemployment for the identification of true state dependence.

restrict our estimation sample to a balanced panel (Column 2) or exclude the Scotland and Wales boost samples (Column 3).[22]

A number of previous studies showed that the estimated true state dependence drops considerably when spells of unemployment lasting across two (or more) consecutive interviews are excluded from the estimation sample (Arulampalam et al., 2000; Stewart, 2007). The check is performed on the grounds that the coefficient on lagged unemployment status is likely to capture the effect of continuing spells rather than true state dependence (Jenkins, 2013). Column 4 of Tables 2.A1-2.A5 reports estimated coefficients and APEs from Model 2 after excluding long spells of unemployment and re-compacting the panel. Consistent with previous literature, the size of the coefficients on lagged unemployment drops considerably and the same applies to APEs. Despite the reduced size, a negative association with the business cycle is still present. It should be noted, however, that the check is costly in terms of observation loss and likely to introduce a negative bias in our calculation. Dropping continuing spells of unemployment implies, in fact, excluding from the estimation sample not only the long spell of unemployment experienced by a respondent, but also all the observations following the long spell as the panel needs to be compact. Although the number of observations lost is not too large in absolute terms, it should be noted that the exclusion only affects those with at least two consecutive unemployment statuses in our estimation sample, i.e., those who contribute to our coefficient of interest.[23] Moreover, from an intuitive point of view, the scarring effect of unemployment can manifest itself not only through an increase in the probability of being in a different

[22] The declining trend in scarring effect observed in the sub-period 1991-1995 is less regular using a balanced panel. It should also be noted that Scotland and Wales boost samples have been introduced only in 1999, and this explains why estimates for the early '90s sub-period reported in Column 3 are the same as to those reported in the main result sub-section.

[23] Consistent with Arulampalam et al. (2000), we consider a spell "long" if the respondent is in the same unemployment spell in two consecutive interviews. Stewart (2007) makes the definition stricter by excluding from the analysis all the observations who are unemployed in consecutive interviews and do not have at least one employment spell in between. This specification leads to a loss of statistical significance for the coefficients on lagged unemployment experience for Waves 1-5 and Waves 16-20, arguably because of the even higher number of observations with two or more consecutive unemployment spells excluded by the check.

unemployment spell in the future, but also through a lower probability of finding a job and ending the current unemployment spell. Hence, arguably, excluding from the estimation sample those with long spells of unemployment would introduce a negative bias in our estimates.[24] Finally, excluding long spells of unemployment would be most appropriate if the time between two consecutive interviews did not allow for a change in employment status. An example can clarify this point. If our models were applied to a study of prison convictions and the gap between interviews was smaller than the time that the respondent has to spend in prison, then we would artificially find a positive effect of a past prison experience on a current prison experience, while the prison experience would, in fact, be the same and the respondent would not have had any chance to change her status. In the context of this paper, respondents are allowed to change their labour market status between consecutive interviews and if they do not change it, it is because of individual characteristics, observable and/or unobservable, labour demand factors, and past unemployment experiences.

To conclude, the checks performed confirm the robustness of our results and support the evidence on the existence of true state dependence in our data and on its negative correlation with the business cycle.[25]

2.4 Conclusions

In this paper we analyse the extent to which past unemployment experiences have affected current unemployment risk in the last two decades.

In the spirit, among others, of Arulampalam et al. (2000) and Stewart (2007), we use data from the BHPS and Understanding Society to estimate a dynamic random effect probit with

[24] Elements of duration dependence, as well as state dependence, can influence the probability of staying in unemployment for two or more consecutive waves. However, explicitly disentangling the two sources of dependence goes beyond the scope of this paper.

[25] We do not report p-values based on bootstrap for concerns relative to computational time.

Wooldridge's (2005) solution to the initial condition problem for three sub periods: the early '90s, the early 2000s and the Great Recession.

Our estimates provide evidence in favour of true state dependence in all the periods analysed, with youth affected the most during the early 2000s and the Great Recession. The age profile of unemployment scarring is less clear in the early 90s sub-period, as youths appear to be less affected than mature workers although the differences are not statistically significant. Consistent with theoretical predictions of job crowding models (Michaillat, 2012; Crépon et al., 2013), we also find a negative association between business cycle and true state dependence, as estimates increase when unemployment increases, and fall when unemployment falls.

A number of studies have already documented that unemployment experiences leave significant and potentially long lasting scars on individual's employability, wages and wellbeing. Both the incidence of unemployment and the duration of an unemployment spell has been shown to matter (see, among others, Arulampalam et al., 2000; Böheim and Taylor, 2002; Stewart, 2007; Bell and Blanchflower, 2011a, b; Clark et al., 2001; Gregory and Jukes, 2001; Arulampalam, 2001). The existing UK based evidence on true state dependence in unemployment incidence is however mostly based on data from the '90s (Arulampalam et al., 2000; Stewart, 2007). Our work hence complements the existing literature not only by providing estimates for more recent years, but also doing so in a consistent and comparable manner across the sub-period analysed.

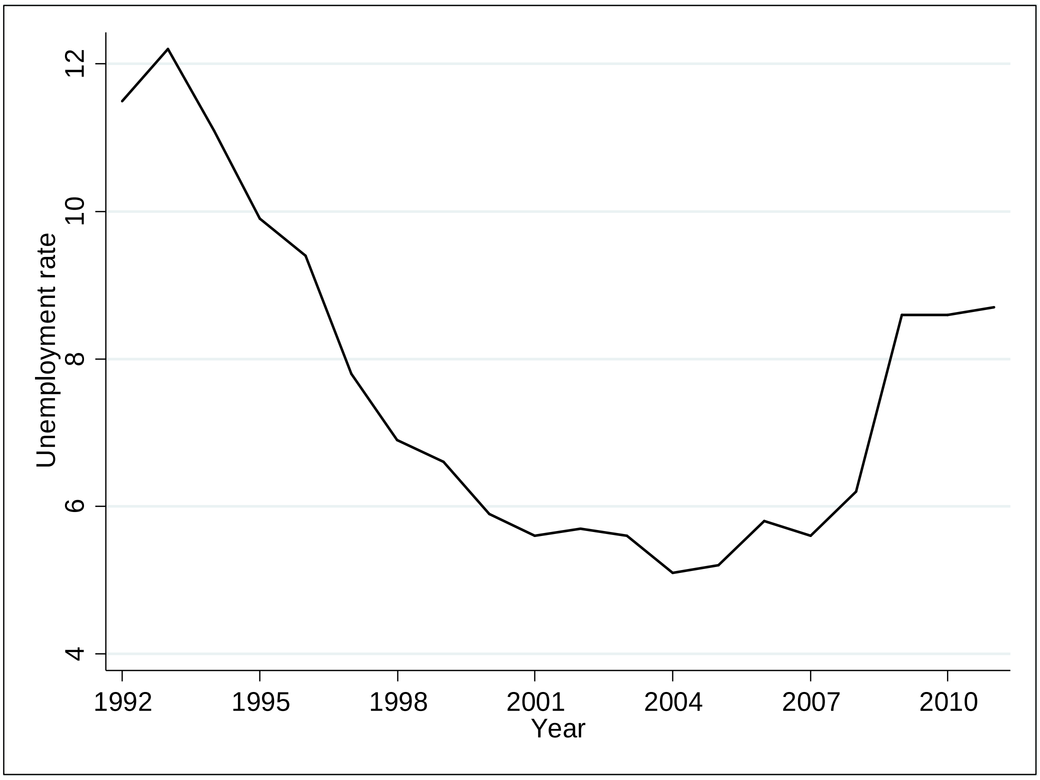
Consistent with Arulampalam et al. (2000) and Stewart (2007), we find in particular that between 1991 and 1995, a period of declining unemployment, those unemployed at a given point in time were, on average, 8.4 percentage points more likely to experience unemployment in the following wave than those previously in employment. Our estimates show a declining pattern of true state dependence in the period analysed, as APEs decline from 9.8 to 6.2 percentage points. We also find evidence of true state dependence between 1999 and 2003/04, a period of low and stable unemployment. In these years, APEs are, on average, equal to 6.2 percentage points, and the pattern of the estimates across waves is basically stable over time. Finally, between 2006 and 2011/12, the period which includes the Great Recession, estimates of true state dependence amount to 7.9 percentage points, increasing over time from 6.9 percentage points in 2007, to 9.9 percentage points in 2010/11, and reducing to 8.4 percentage points in 2011/12.

Our analysis also suggests that unemployment experiences scars more if labour market conditions are less favourable. The finding add to the existing literature as previous UK based evidence on the relationship between unemployment scarring and business cycle is scarce and focused on duration dependence rather than state dependence. Kalwij (2010) show evidence of true duration dependence being negatively associated with the business cycle only if the model does not control for compositional effects in the unemployment inflows. The result is consistent with Turon (2003), which reports evidence on genuine duration dependence not varying significantly over the business cycle. Both papers employ proportional hazard models, and differences in the methodologies adopted to disentangle the role "true" state dependence from that of observed and unobserved heterogeneity, as well as in the data used, are a likely explanation for the different result found in our analysis.

Our findings therefore support the existence of a scarring effect of unemployment during the Great Recession, and a positive association arises with levels of unemployment. The Great Recession has, therefore, not only increased the current stock of unemployed, but also negatively influenced the future employment chances of those experiencing unemployment. Thus, short-term interventions aimed at reducing the number of unemployed are likely to have beneficial effects both in the short and in the medium-long term.

2.5 Tables and Figures

Figure 2.1: Unemployment Rate in Great Britain, males only, 1992-2011



Source: ONS Labour market statistics

Figure 2.2: Unemployment rate and True state dependence, 1992-2011

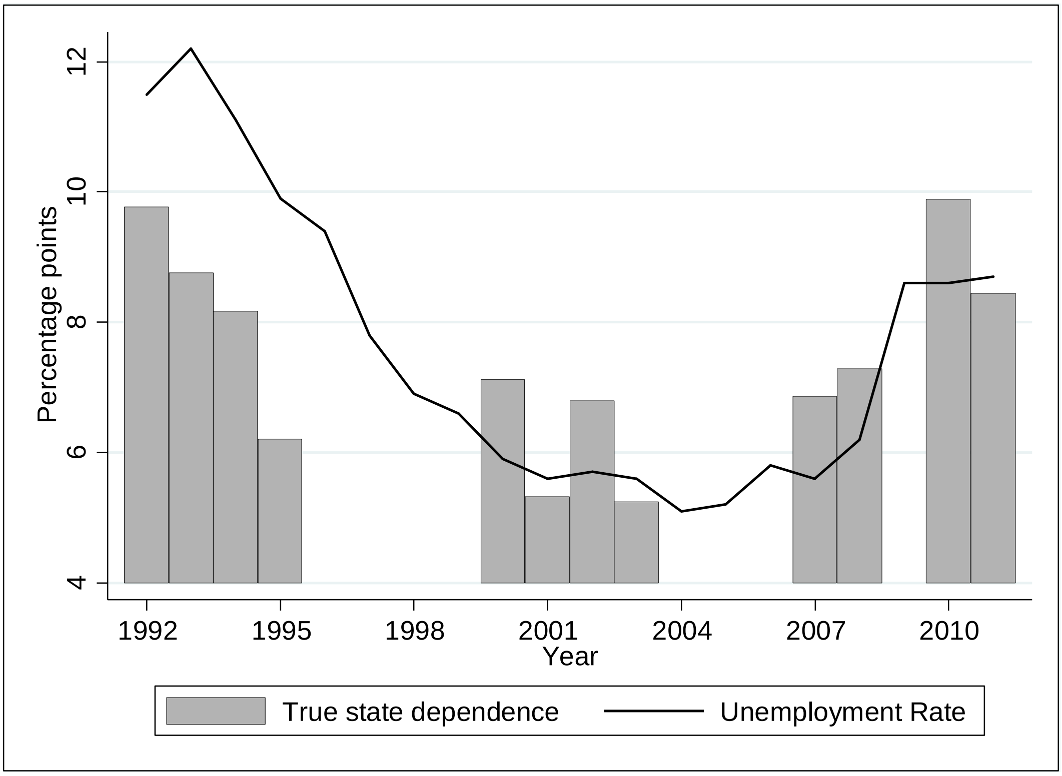
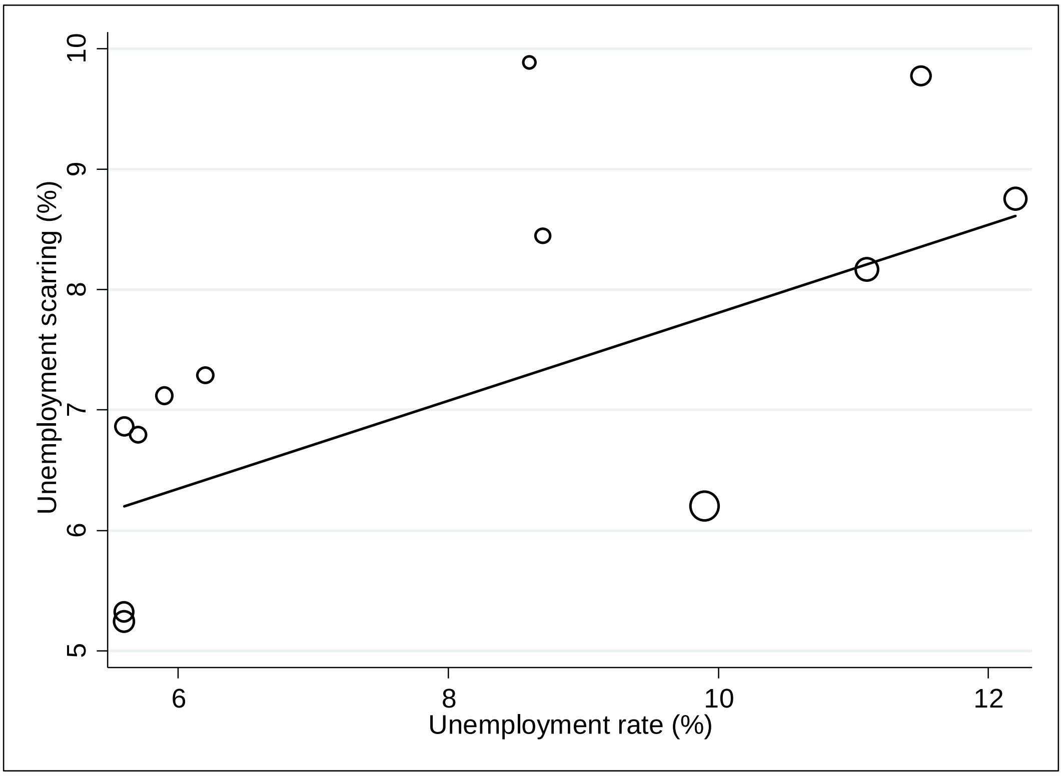


Figure 2.3: Unemployment Rate and True state dependence, scatterplot



Note: Point estimates are weighted by the inverse of their estimated variance

Table 2.1: Descriptive statistics, Waves 1-5

	1	2	3	4	5	Total
Unemployed	0.096	0.079	0.066	0.058	0.038	0.071
Unemployed (t-1)	.	0.077	0.066	0.058	0.048	0.064
Unemployed | Unemployed t-1	.	0.556	0.587	0.600	0.507	0.566
Unemployed | Employed t-1	.	0.039	0.029	0.025	0.014	0.028
Age 16-25	0.235	0.175	0.145	0.113	0.090	0.162
Age 26-35	0.338	0.349	0.345	0.330	0.313	0.337
Age 36-45	0.298	0.323	0.311	0.319	0.328	0.314
Age 46-55	0.128	0.153	0.199	0.237	0.269	0.188
Claimant proportion	6.360	7.332	7.271	6.331	5.624	6.622
Degree or higher	0.116	0.121	0.131	0.137	0.137	0.127
Other high	0.067	0.069	0.072	0.074	0.075	0.071
A level	0.223	0.229	0.226	0.227	0.230	0.227
O level	0.273	0.269	0.268	0.267	0.269	0.269
CSE level	0.077	0.077	0.080	0.078	0.077	0.078
None of these	0.244	0.235	0.224	0.217	0.211	0.228
Home owner	0.753	0.787	0.791	0.812	0.831	0.790
Social renter	0.144	0.131	0.125	0.107	0.089	0.123
Private renter	0.104	0.081	0.085	0.081	0.080	0.088
Married	0.588	0.640	0.666	0.677	0.694	0.646
Number of children in HH	0.855	0.888	0.889	0.886	0.876	0.877
Poor health	0.033	0.037	0.035	0.034	0.030	0.034
Non white	0.041	0.031	0.031	0.031	0.027	0.033
London and SE	0.242	0.231	0.235	0.233	0.232	0.235
South West	0.089	0.093	0.094	0.093	0.092	0.092
East of England	0.084	0.087	0.089	0.090	0.092	0.088
Midlands	0.177	0.182	0.182	0.185	0.188	0.182
North, Yorkshire and the Humber	0.272	0.271	0.262	0.263	0.267	0.267
Wales	0.050	0.051	0.051	0.053	0.050	0.051
Scotland	0.087	0.085	0.087	0.083	0.080	0.085
N	2705	2186	1895	1727	1571	10084

Table 2.2: Descriptive statistics, Waves 9-13

	9	10	11	12	13	Total
Unemployed	0.057	0.038	0.024	0.027	0.019	0.035
Unemployed (t-1)	.	0.041	0.028	0.017	0.022	0.028
Unemployed | Unemployed t-1	.	0.496	0.429	0.538	0.304	0.452
Unemployed | Employed t-1	.	0.019	0.013	0.018	0.012	0.016
Age 16-25	0.212	0.159	0.111	0.091	0.063	0.136
Age 26-35	0.339	0.338	0.328	0.305	0.285	0.322
Age 36-45	0.332	0.351	0.373	0.378	0.379	0.360
Age 46-55	0.117	0.152	0.189	0.226	0.273	0.183
Claimant proportion	3.170	2.709	2.428	2.325	2.226	2.626
Degree or higher	0.171	0.175	0.180	0.186	0.192	0.180
Other high	0.086	0.091	0.093	0.093	0.093	0.091
A level	0.251	0.254	0.252	0.255	0.256	0.253
O level	0.269	0.271	0.270	0.270	0.269	0.270
CSE level	0.081	0.076	0.075	0.074	0.072	0.076
None of these	0.143	0.133	0.128	0.123	0.118	0.131
Home owner	0.760	0.794	0.816	0.836	0.852	0.806
Social renter	0.143	0.124	0.109	0.098	0.082	0.114
Private renter	0.098	0.081	0.076	0.066	0.065	0.079
Married	0.511	0.557	0.593	0.617	0.636	0.576
Number of children in HH	0.835	0.886	0.898	0.901	0.890	0.879
Poor health	0.012	0.041	0.037	0.041	0.039	0.033
Non white	0.032	0.032	0.032	0.030	0.030	0.031
London and SE	0.161	0.162	0.165	0.160	0.160	0.162
South West	0.063	0.065	0.065	0.071	0.070	0.066
East of England	0.063	0.067	0.066	0.069	0.073	0.067
Midlands	0.124	0.129	0.131	0.136	0.138	0.131
North, Yorkshire and the Humber	0.181	0.188	0.192	0.193	0.192	0.188
Wales	0.190	0.175	0.174	0.167	0.160	0.175
Scotland	0.218	0.214	0.208	0.205	0.208	0.211
N	3287	2835	2540	2290	2081	13033

Table 2.3: Descriptive statistics, Waves 16-20

	16	17	18	19	20	Total
Unemployed	0.046	0.025	0.021	0.028	0.025	0.031
Unemployed t-1	.	0.035	0.020	0.017	0.026	0.025
Unemployed | Unemployed t-1	.	0.381	0.442	0.407	0.429	0.407
Unemployed | Employed t-1	.	0.012	0.013	0.022	0.014	0.015
Age 16-25	0.189	0.138	0.103	0.052	0.026	0.116
Age 26-35	0.311	0.299	0.289	0.252	0.222	0.282
Age 36-45	0.347	0.368	0.368	0.381	0.384	0.366
Age 46-55	0.153	0.195	0.241	0.315	0.368	0.235
Claimant proportion	2.259	1.896	2.327	3.503	3.569	2.557
Degree or higher	0.204	0.216	0.225	0.245	0.258	0.225
Other high	0.085	0.084	0.083	0.087	0.088	0.085
A level	0.261	0.256	0.257	0.262	0.253	0.258
O level	0.278	0.277	0.271	0.254	0.252	0.269
CSE level	0.080	0.077	0.077	0.071	0.076	0.077
None of these	0.092	0.089	0.087	0.079	0.073	0.086
Home owner	0.775	0.798	0.808	0.820	0.830	0.802
Social renter	0.117	0.108	0.094	0.089	0.076	0.100
Private renter	0.108	0.094	0.098	0.091	0.094	0.098
Married	0.480	0.528	0.564	0.608	0.645	0.551
Number of children in HH	0.826	0.836	0.845	0.880	0.891	0.849
Poor health	0.034	0.034	0.037	0.011	0.012	0.028
Non white	0.033	0.032	0.031	0.034	0.035	0.033
London and SE	0.154	0.155	0.157	0.163	0.166	0.158
South West	0.067	0.068	0.068	0.070	0.076	0.069
East of England	0.066	0.068	0.069	0.071	0.072	0.069
Midlands	0.125	0.125	0.126	0.127	0.128	0.126
North, Yorkshire and the Humber	0.203	0.200	0.207	0.201	0.197	0.202
Wales	0.184	0.183	0.176	0.171	0.171	0.178
Scotland	0.202	0.200	0.198	0.196	0.190	0.198
N	2739	2375	2144	1581	1363	10202

Table 2.4: Model estimates, Waves 1-5

	(1) Pooled probit	(2) Wooldridge	(3) Unempl inter	(4) Age inter
Unemployed t-1	1.788***	0.909***	0.425	0.571**
	(0.071)	(0.153)	(0.384)	(0.224)
Claimant proportion	0.038***	0.167**	0.156**	0.175***
	(0.013)	(0.067)	(0.067)	(0.067)
Unemployed t-1 * Claimant proportion			0.067	
			(0.048)	
Age 26-35	-0.281***	-0.392***	-0.393***	-0.520***
	(0.087)	(0.135)	(0.136)	(0.150)
Age 35-45	-0.299***	-0.432***	-0.431***	-0.524***
	(0.096)	(0.153)	(0.155)	(0.163)
Age 46-55	-0.067	-0.087	-0.085	-0.248
	(0.106)	(0.170)	(0.172)	(0.181)
Unemployed t-1* Age 26-35				0.450*
				(0.238)
Unemployed t-1* Age 36-45				0.280
				(0.259)
Unemployed t-1* Age 46-55				0.762**
				(0.301)
Wave 2 (Ref.)				
Wave 3	-0.064	-0.101	-0.099	-0.086
	(0.073)	(0.090)	(0.091)	(0.090)
Wave 4	-0.070	0.007	0.006	0.015
	(0.079)	(0.113)	(0.114)	(0.114)
Wave 5	-0.250***	-0.129	-0.120	-0.130
	(0.092)	(0.150)	(0.151)	(0.150)
Degree or higher (Ref)				
Other high	0.093	0.080	0.080	0.080
	(0.185)	(0.288)	(0.292)	(0.288)
A level	0.338***	0.522**	0.522**	0.503**
	(0.131)	(0.209)	(0.212)	(0.210)
O level	0.350***	0.462**	0.468**	0.441**
	(0.129)	(0.204)	(0.207)	(0.205)
CSE level	0.453***	0.624***	0.627**	0.616**
	(0.149)	(0.241)	(0.245)	(0.242)
None of these	0.509***	0.693***	0.698***	0.690***
	(0.128)	(0.208)	(0.211)	(0.209)
Private renters (Ref)				
Home owner	-0.218**	-0.313	-0.320	-0.335
	(0.099)	(0.278)	(0.280)	(0.278)
Social renter	0.273**	0.076	0.062	0.036
	(0.111)	(0.320)	(0.323)	(0.320)
Married	-0.292***	-0.248	-0.255	-0.229
	(0.078)	(0.284)	(0.286)	(0.283)
Number of children in HH	0.134***	-0.009	-0.011	-0.006
	(0.030)	(0.101)	(0.102)	(0.102)
Poor-V poor health	0.180	0.012	0.011	0.014
	(0.144)	(0.257)	(0.259)	(0.258)
Non white	0.110	0.183	0.172	0.171
	(0.156)	(0.255)	(0.262)	(0.256)
Initial condition		1.309***	1.348***	1.333***
		(0.246)	(0.518)	(0.249)
Initial condition * Avg. Claimant prop			-0.006	
			(0.065)	
_cons	-2.123***	-3.033***	-2.984***	-2.953***
	(0.197)	(0.379)	(0.388)	(0.380)
lnsig2u		-0.080	-0.038	-0.076
		(0.290)	(0.286)	(0.293)
Region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	No	Yes	Yes	Yes
N	7379	7379	7379	7379

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: APEs on lagged unemployment, Waves 1-5

	(1)		(2)		(3)		(4)	
	APE	pvalue*	APE	pvalue**	APE	pvalue**	APE	pvalue**
Wave 2	0.425	0.000	0.098	0.001	0.101	0.000	0.100	0.001
Wave 3	0.401	0.000	0.088	0.000	0.090	0.000	0.095	0.001
Wave 4	0.383	0.000	0.082	0.001	0.077	0.001	0.091	0.001
Wave 5	0.314	0.000	0.062	0.001	0.055	0.002	0.071	0.001
Total	0.385	0.000	0.084	0.000	0.083	0.000	0.090	0.001

Note: *standard errors based on delta methods; **Bootstrapped standard errors, 500 replications

Table 2.6: APEs on lagged unemployment by claimant proportion, Waves 1-5

	(2)	
	APE	pvalue*
Claimant proportion %		
2-4	0.057	0.002
4-6	0.073	0.001
6-8	0.088	0.000
8-10	0.098	0.000
10-12	0.107	0.000
12-14	0.115	0.000
14+	0.124	0.001
Test 4-6 vs 2-4	0.016	0.004
Test 6-8 vs 2-4	0.031	0.001
Test 8-10 vs 2-4	0.041	0.001
Test 10-12 vs 2-4	0.051	0.001
Test 12-14 vs 2-4	0.058	0.003
Test 14+ vs 2-4	0.067	0.008

*Bootstrapped standard errors, 500 replications

Table 2.7: APEs on lagged unemployment by age, Waves 1-5

	(2)		(4)	
	APE	pvalue*	APE	pvalue*
Age 16-25	0.138	0.000	0.082	0.047
Age 26-35	0.079	0.001	0.091	0.001
Age 36-45	0.070	0.001	0.064	0.013
Age 46-55	0.078	0.002	0.134	0.010
Test 26-35 vs 16-25	-0.059	0.000	0.009	0.801
Test 36-45 vs 16-25	-0.068	0.000	-0.018	0.633
Test 46-55 vs 16-25	-0.060	0.000	0.052	0.329

* Bootstrapped standard errors, 500 replications

Table 2.8: Model estimates, Waves 9-13

	(1) Pooled probit	(2) Wooldridge	(3) Unempl inter	(4) Age inter
Unemployed t-1	1.712***	0.894***	0.843**	0.821***
	(0.090)	(0.187)	(0.389)	(0.245)
Claimant proportion	0.071**	-0.092	-0.095	-0.101
	(0.030)	(0.119)	(0.120)	(0.118)
Unemployed t-1 * Claimant proportion			0.018	
			(0.121)	
Age 26-35	-0.285***	-0.361***	-0.362***	-0.367***
	(0.092)	(0.124)	(0.124)	(0.131)
Age 35-45	-0.273***	-0.305**	-0.306**	-0.303**
	(0.098)	(0.130)	(0.131)	(0.136)
Age 46-55	-0.233**	-0.239	-0.239	-0.306*
	(0.113)	(0.149)	(0.150)	(0.158)
Unemployed t-1* Age 26-35				0.052
				(0.275)
Unemployed t-1* Age 36-45				-0.037
				(0.292)
Unemployed t-1* Age 46-55				0.535
				(0.333)
Wave 10 (Ref.)				
Wave 11	-0.124	-0.199*	-0.200*	-0.203*
	(0.086)	(0.104)	(0.104)	(0.104)
Wave 12	0.089	0.028	0.028	0.031
	(0.085)	(0.105)	(0.105)	(0.104)
Wave 13	-0.085	-0.152	-0.152	-0.163
	(0.096)	(0.122)	(0.122)	(0.122)
Degree or higher (Ref)				
Other high	0.124	0.173	0.173	0.165
	(0.132)	(0.173)	(0.173)	(0.171)
A level	-0.143	-0.136	-0.137	-0.133
	(0.114)	(0.147)	(0.148)	(0.145)
O level	0.021	0.039	0.038	0.041
	(0.106)	(0.138)	(0.139)	(0.137)
CSE level	0.061	0.075	0.075	0.074
	(0.142)	(0.188)	(0.189)	(0.185)
None of these	0.305***	0.366**	0.367**	0.356**
	(0.113)	(0.153)	(0.154)	(0.152)
Private renters (Ref)				
Home owner	-0.203*	0.058	0.061	0.047
	(0.108)	(0.250)	(0.251)	(0.247)
Social renter	0.290**	-0.018	-0.016	-0.036
	(0.120)	(0.293)	(0.293)	(0.291)
Married	-0.326***	-0.158	-0.156	-0.167
	(0.079)	(0.270)	(0.271)	(0.269)
Number of children in HH	-0.048	0.059	0.059	0.059
	(0.036)	(0.115)	(0.115)	(0.114)
Poor-V poor health	0.180	0.191	0.190	0.195
	(0.137)	(0.241)	(0.241)	(0.239)
Non white	0.299*	0.370*	0.372*	0.364*
	(0.163)	(0.217)	(0.217)	(0.214)
Initial condition		1.146***	1.160***	1.126***
		(0.252)	(0.450)	(0.250)
Initial condition * Avg. Claimant prop			-0.003	
			(0.134)	
_cons	-2.008***	-2.504***	-2.503***	-2.478***
	(0.175)	(0.292)	(0.293)	(0.290)
lnsig2u		-0.817*	-0.804*	-0.888*
		(0.442)	(0.446)	(0.461)
Region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	No	Yes	Yes	Yes
N	9746	9746	9746	9746

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: APEs on lagged unemployment, Waves 9-13

	(1)		(2)		(3)		(4)	
	APE	pvalue*	APE	pvalue**	APE	pvalue**	APE	pvalue**
Wave 10	0.300	0.000	0.071	0.025	0.071	0.031	0.075	0.026
Wave 11	0.249	0.000	0.053	0.056	0.053	0.075	0.059	0.055
Wave 12	0.300	0.000	0.068	0.044	0.067	0.065	0.078	0.039
Wave 13	0.242	0.000	0.052	0.048	0.052	0.075	0.062	0.044
Total	0.274	0.000	0.062	0.037	0.061	0.052	0.069	0.035

Note: *standard errors based on delta methods; **Bootstrapped standard errors, 500 replications

Table 2.10: APEs on lagged unemployment by claimant proportion, Waves 9-13

	(2)	
	APE	pvalue*
Claimant proportion %		
0-2	0.047	0.056
2-4	0.067	0.034
4-6	0.089	0.023
6+	0.102	0.033
Test 2-4 vs 0-2	0.020	0.026
Test 4-6 vs 0-2	0.042	0.017
Test 6+ vs 0-2	0.054	0.079

*Bootstrapped standard errors, 500 replications

Table 2.11: APEs on lagged unemployment by age, Waves 9-13

	(2)		(4)	
	APE	pvalue*	APE	pvalue*
Age 16-25	0.122	0.015	0.112	0.045
Age 26-35	0.056	0.043	0.055	0.121
Age 36-45	0.051	0.059	0.042	0.130
Age 46-55	0.058	0.048	0.115	0.042
Test 26-35 vs 16-25	-0.066	0.009	-0.056	0.194
Test 36-45 vs 16-25	-0.072	0.005	-0.069	0.116
Test 46-55 vs 16-25	-0.065	0.009	0.003	0.949

* Bootstrapped standard errors, 500 replications

Table 2.12: Model estimates, Waves 16-20

	(1) Pooled probit	(2) Wooldridge	(3) Unempl inter	(4) Age inter
Unemployed t-1	1.506***	1.016***	1.111***	0.944***
	(0.110)	(0.206)	(0.373)	(0.258)
Claimant proportion	0.054	0.020	0.031	0.021
	(0.038)	(0.097)	(0.099)	(0.096)
Unemployed t-1 * Claimant proportion			-0.035	
			(0.112)	
Age 26-35	-0.231**	-0.242*	-0.244*	-0.275*
	(0.114)	(0.131)	(0.132)	(0.143)
Age 35-45	-0.384***	-0.409***	-0.417***	-0.431***
	(0.120)	(0.143)	(0.144)	(0.152)
Age 46-55	-0.373***	-0.386**	-0.395**	-0.410**
	(0.136)	(0.160)	(0.161)	(0.168)
Unemployed t-1* Age 26-35				0.159
				(0.305)
Unemployed t-1* Age 36-45				0.096
				(0.330)
Unemployed t-1* Age 46-55				0.108
				(0.397)
Wave 17 (Ref.)				
Wave 18	0.075	0.096	0.093	0.096
	(0.104)	(0.120)	(0.120)	(0.120)
Wave 19	0.285**	0.381**	0.373**	0.380**
	(0.125)	(0.188)	(0.188)	(0.187)
Wave 20	0.190	0.305	0.304	0.304
	(0.137)	(0.202)	(0.202)	(0.202)
Degree or higher (Ref)				
Other high	0.049	0.079	0.087	0.076
	(0.187)	(0.211)	(0.211)	(0.209)
A level	0.089	0.071	0.076	0.069
	(0.129)	(0.149)	(0.149)	(0.147)
O level	0.110	0.106	0.114	0.102
	(0.126)	(0.144)	(0.145)	(0.143)
CSE level	-0.013	-0.019	-0.018	-0.023
	(0.177)	(0.203)	(0.205)	(0.201)
None of these	0.464***	0.494***	0.509***	0.487***
	(0.143)	(0.169)	(0.170)	(0.168)
Private renters (Ref)				
Home owner	-0.193*	0.084	0.083	0.082
	(0.117)	(0.246)	(0.247)	(0.245)
Social renter	0.419***	0.135	0.145	0.144
	(0.128)	(0.320)	(0.321)	(0.319)
Married	-0.462***	-0.395	-0.409	-0.393
	(0.098)	(0.318)	(0.318)	(0.317)
Number of children in HH	0.103***	0.041	0.044	0.045
	(0.039)	(0.106)	(0.107)	(0.106)
Poor-V poor health	0.395**	0.151	0.153	0.146
	(0.179)	(0.276)	(0.275)	(0.275)
Non white	0.217	0.220	0.231	0.219
	(0.198)	(0.229)	(0.231)	(0.228)
Initial condition		0.710***	0.046	0.698***
		(0.243)	(0.496)	(0.242)
Initial condition * Avg. Claimant prop			0.233	
			(0.158)	
_cons	-2.267***	-2.516***	-2.453***	-2.477***
	(0.209)	(0.312)	(0.315)	(0.318)
lnsig2u		-1.567**	-1.539**	-1.652**
		(0.756)	(0.751)	(0.826)
Region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	No	Yes	Yes	Yes
N	7463	7463	7463	7463

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13: APEs on lagged unemployment, Waves 16-20

	(1)		(2)		(3)		(4)	
	APE	pvalue*	APE	pvalue**	APE	pvalue**	APE	pvalue**
Wave 17	0.175	0.000	0.069	0.020	0.071	0.031	0.072	0.023
Wave 18	0.187	0.000	0.073	0.034	0.074	0.038	0.077	0.043
Wave 19	0.237	0.000	0.099	0.023	0.094	0.026	0.106	0.033
Wave 20	0.205	0.000	0.084	0.022	0.080	0.029	0.091	0.040
Total	0.197	0.000	0.079	0.021	0.078	0.022	0.084	0.029

Note: *standard errors based on delta methods; **Bootstrapped standard errors, 500 replications

Table 2.14: APEs on lagged unemployment by claimant proportion, Waves 16-20

	(2)	
	APE	pvalue*
Claimant proportion %		
0-2	0.063	0.034
2-4	0.082	0.020
4-6	0.102	0.016
6+	0.114	0.020
Test 2-4 vs 0-2	0.019	0.021
Test 4-6 vs 0-2	0.039	0.026
Test 6+ vs 0-2	0.051	0.056

*Bootstrapped standard errors, 500 replications

Table 2.15: APEs on lagged unemployment by age, Waves 16-20

	(2)		(4)	
	APE	pvalue*	APE	pvalue*
Age 16-25	0.159	0.008	0.147	0.021
Age 26-35	0.092	0.018	0.106	0.066
Age 36-45	0.064	0.036	0.068	0.123
Age 46-55	0.060	0.046	0.065	0.273
Test 26-35 vs 16-25	-0.067	0.015	-0.041	0.503
Test 36-45 vs 16-25	-0.095	0.004	-0.079	0.213
Test 46-55 vs 16-25	-0.099	0.005	-0.082	0.255

* Bootstrapped standard errors, 500 replications

Table 2.16: APEs at fixed values of covariates after Model 2, Waves 1-5

	State Dependence	Pvalue
Wave 2	0.117	0.007
Wave 3	0.106	0.009
Wave 4	0.101	0.011
Wave 5	0.079	0.019

Note: Bootstrapped standard errors, 500 replications. Covariates are fixed at the following values: aged between 16 and 25; O-level education; home owners; non married and with no children; not in poor health; from a white ethnic background, and living in the Midlands. Claimant proportion is fixed at the wave specific average faced by people living in the Midlands.

Table 2.17: APEs at fixed values of covariates after Model 2, Waves 9-13

	State Dependence	Pvalue
Wave 10	0.080	0.092
Wave 11	0.065	0.137
Wave 12	0.087	0.103
Wave 13	0.071	0.116

Note: Bootstrapped standard errors, 500 replications. Covariates are fixed at the following values: aged between 16 and 25; O-level education; home owners; non married and with no children; not in poor health; from a white ethnic background, and living in the Midlands. Claimant proportion is fixed at the wave specific average faced by people living in the Midlands.

Table 2.18: APEs at fixed values of covariates after Model 2, Waves 16-20

	State Dependence	Pvalue
Wave 17	0.111	0.068
Wave 18	0.126	0.076
Wave 19	0.176	0.035
Wave 20	0.163	0.037

Note: Bootstrapped standard errors, 500 replications. Covariates are fixed at the following values: aged between 16 and 25; O-level education; home owners; non married and with no children; not in poor health; from a white ethnic background, and living in the Midlands. Claimant proportion is fixed at the wave specific average faced by people living in the Midlands.

2.6 Appendix: Complementary Tables

Table 2.A1: Robustness checks, Model 2, Waves 1-5

	(1) Alternative active definition	(2) Balanced panel	(3) Essex sample	(4) No long spell
Unemployed t-1	0.982***	0.853***	0.909***	0.422**
	(0.136)	(0.170)	(0.153)	(0.194)
Claimant proportion	0.148**	0.206***	0.167**	0.077
	(0.060)	(0.077)	(0.067)	(0.071)
Age 26-35	-0.276**	-0.315*	-0.392***	-0.442***
	(0.123)	(0.163)	(0.135)	(0.134)
Age 35-45	-0.252*	-0.570***	-0.432***	-0.469***
	(0.139)	(0.195)	(0.153)	(0.148)
Age 46-55	0.068	-0.113	-0.087	-0.158
	(0.157)	(0.206)	(0.170)	(0.162)
Wave 2 (Ref.)				
Wave 3	-0.071	-0.058	-0.101	-0.068
	(0.083)	(0.115)	(0.090)	(0.091)
Wave 4	-0.012	0.212	0.007	-0.107
	(0.103)	(0.136)	(0.113)	(0.120)
Wave 5	-0.117	0.113	-0.129	-0.339**
	(0.135)	(0.172)	(0.150)	(0.162)
Degree or higher (Ref)				
Other high	0.068	0.029	0.080	0.056
	(0.254)	(0.377)	(0.288)	(0.255)
A level	0.399**	0.766***	0.522**	0.407**
	(0.185)	(0.261)	(0.209)	(0.186)
O level	0.362**	0.572**	0.462**	0.350*
	(0.181)	(0.256)	(0.204)	(0.182)
CSE level	0.495**	0.702**	0.624***	0.401*
	(0.219)	(0.296)	(0.241)	(0.222)
None of these	0.621***	0.950***	0.693***	0.461**
	(0.184)	(0.265)	(0.208)	(0.187)
Private renters (Ref)				
Home owner	-0.402	-0.507*	-0.313	-0.344
	(0.259)	(0.306)	(0.278)	(0.289)
Social renter	0.009	-0.031	0.076	-0.069
	(0.295)	(0.366)	(0.320)	(0.338)
Married	-0.158	-0.334	-0.248	-0.287
	(0.241)	(0.318)	(0.284)	(0.289)
Number of children in HH	0.028	0.141	-0.009	-0.044
	(0.093)	(0.121)	(0.101)	(0.107)
Poor-V poor health	0.258	-0.044	0.012	0.079
	(0.220)	(0.319)	(0.257)	(0.270)
Non white	0.277	-0.151	0.183	0.151
	(0.220)	(0.368)	(0.255)	(0.245)
Initial condition	1.321***	1.194***	1.309***	0.716***
	(0.221)	(0.249)	(0.246)	(0.226)
_cons	-2.792***	-3.297***	-3.033***	-2.735***
	(0.326)	(0.446)	(0.379)	(0.367)
lnsig2u	-0.119	-0.147	-0.080	-0.529
	(0.257)	(0.309)	(0.290)	(0.412)
Region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	Yes	Yes	Yes	Yes
N	7585	6284	7379	7110

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A2: APEs after robustness checks, Waves 1-5

	(1) APE	(2) APE	(3) APE	(4) APE
Wave 2	0.121	0.069	0.098	0.037
Wave 3	0.113	0.064	0.088	0.033
Wave 4	0.104	0.069	0.082	0.028
Wave 5	0.085	0.054	0.062	0.018
Total	0.107	0.064	0.084	0.030

Table 2.A3: Robustness checks, Model 2, Waves 9-13

	(1) Alternative active definition	(2) Balanced panel	(3) Essex sample	(4) No long spell
Unemployed t-1	0.881***	0.919***	0.920***	0.444**
	(0.159)	(0.217)	(0.237)	(0.218)
Claimant proportion	0.001	0.084	-0.092	-0.189
	(0.113)	(0.151)	(0.139)	(0.125)
Age 26-35	-0.290**	-0.344**	-0.198	-0.415***
	(0.124)	(0.155)	(0.152)	(0.131)
Age 35-45	-0.259*	-0.266	-0.285*	-0.342**
	(0.134)	(0.163)	(0.170)	(0.138)
Age 46-55	-0.153	-0.154	-0.137	-0.323**
	(0.154)	(0.181)	(0.186)	(0.160)
Wave 10 (Ref.)				
Wave 11	-0.094	-0.309**	0.007	-0.224**
	(0.098)	(0.153)	(0.130)	(0.110)
Wave 12	0.078	0.239*	0.132	0.018
	(0.103)	(0.133)	(0.133)	(0.111)
Wave 13	-0.033	0.084	-0.009	-0.167
	(0.116)	(0.147)	(0.148)	(0.129)
Degree or higher (Ref)				
Other high	0.159	0.209	0.351	0.152
	(0.187)	(0.194)	(0.213)	(0.183)
A level	-0.033	-0.117	-0.154	-0.107
	(0.153)	(0.167)	(0.188)	(0.153)
O level	0.070	-0.103	0.032	0.034
	(0.148)	(0.163)	(0.173)	(0.146)
CSE level	0.189	-0.099	0.194	0.105
	(0.196)	(0.237)	(0.217)	(0.196)
None of these	0.445***	0.206	0.427**	0.338**
	(0.161)	(0.184)	(0.197)	(0.163)
Private renters (Ref)				
Home owner	0.088	0.179	0.163	-0.030
	(0.247)	(0.297)	(0.311)	(0.273)
Social renter	-0.149	0.668*	0.344	-0.057
	(0.278)	(0.380)	(0.367)	(0.331)
Married	0.227	-0.130	0.023	-0.213
	(0.239)	(0.313)	(0.309)	(0.280)
Number of children in HH	0.017	-0.248*	0.137	0.045
	(0.101)	(0.141)	(0.143)	(0.122)
Poor-V poor health	0.226	0.275	0.344	0.097
	(0.208)	(0.305)	(0.299)	(0.255)
Non white	0.451**	-0.017	0.205	0.407*
	(0.218)	(0.334)	(0.250)	(0.224)
Initial condition	1.461***	1.124***	1.090***	0.982***
	(0.240)	(0.264)	(0.311)	(0.260)
_cons	-2.901***	-2.435***	-2.753***	-2.685***
	(0.307)	(0.326)	(0.371)	(0.329)
lnsig2u	-0.357	-0.912*	-0.844	-0.725
	(0.309)	(0.483)	(0.569)	(0.465)
Region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	Yes	Yes	Yes	Yes
N	9948	8324	7002	9640

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A4: APEs after robustness checks, Waves 9-13

	(1) APE	(2) APE	(3) APE	(4) APE
Wave 10	0.068	0.051	0.057	0.024
Wave 11	0.059	0.031	0.056	0.017
Wave 12	0.067	0.066	0.065	0.023
Wave 13	0.058	0.053	0.052	0.018
Total	0.063	0.050	0.058	0.021

Table 2.A5: Robustness checks, Model 2, Waves 16-20

	(1) Alternative active definition	(2) Balanced panel	(3) Essex sample	(4) No long spell
Unemployed t-1	0.858***	1.029***	1.248***	0.550**
	(0.178)	(0.261)	(0.259)	(0.231)
Claimant proportion	0.010	-0.080	0.095	0.106
	(0.092)	(0.135)	(0.118)	(0.093)
Age 26-35	-0.173	-0.195	-0.183	-0.334***
	(0.134)	(0.190)	(0.161)	(0.126)
Age 35-45	-0.276*	-0.308	-0.238	-0.482***
	(0.143)	(0.195)	(0.168)	(0.136)
Age 46-55	-0.355**	-0.320	-0.282	-0.511***
	(0.164)	(0.210)	(0.190)	(0.154)
Wave 17 (Ref.)				
Wave 18	0.121	0.234	0.152	-0.001
	(0.112)	(0.175)	(0.142)	(0.120)
Wave 19	0.416**	0.599**	0.274	0.222
	(0.182)	(0.279)	(0.217)	(0.181)
Wave 20	0.341*	0.550*	0.027	0.125
	(0.195)	(0.293)	(0.241)	(0.194)
Degree or higher (Ref)				
Other high	0.125	0.269	0.386*	0.035
	(0.214)	(0.228)	(0.230)	(0.195)
A level	0.107	0.068	0.178	0.016
	(0.153)	(0.182)	(0.182)	(0.137)
O level	0.135	0.222	0.268	0.070
	(0.149)	(0.170)	(0.173)	(0.133)
CSE level	0.041	0.125	-0.051	-0.107
	(0.207)	(0.241)	(0.252)	(0.195)
None of these	0.542***	0.482**	0.474**	0.446***
	(0.177)	(0.212)	(0.210)	(0.156)
Private renters (Ref)				
Home owner	-0.020	0.143	0.096	0.032
	(0.233)	(0.286)	(0.279)	(0.237)
Social renter	-0.054	0.129	0.327	0.171
	(0.272)	(0.424)	(0.373)	(0.328)
Married	-0.376	-0.172	-0.482	-0.543*
	(0.306)	(0.347)	(0.380)	(0.311)
Number of children in HH	0.013	-0.066	0.110	-0.007
	(0.100)	(0.128)	(0.132)	(0.108)
Poor-V poor health	-0.058	-0.310	0.218	0.128
	(0.241)	(0.372)	(0.361)	(0.287)
Non white	0.401*	0.342	0.079	0.234
	(0.223)	(0.260)	(0.257)	(0.215)
Initial condition	1.281***	0.773***	0.562*	0.427*
	(0.245)	(0.286)	(0.294)	(0.228)
_cons	-2.781***	-2.715***	-2.278***	-2.081***
	(0.324)	(0.424)	(0.344)	(0.282)
lnsig2u	-0.702*	-1.686*	-2.433	-2.811
	(0.397)	(0.949)	(1.893)	(2.096)
Region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	Yes	Yes	Yes	Yes
N	7637	5452	5256	7397

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A6: APEs after robustness checks, Waves 16-20

	(1) APE	(2) APE	(3) APE	(4) APE
Wave 17	0.056	0.052	0.099	0.028
Wave 18	0.060	0.068	0.121	0.027
Wave 19	0.078	0.096	0.149	0.041
Wave 20	0.068	0.088	0.103	0.032
Total	0.064	0.076	0.117	0.031

Chapter 3

Retirement and Cognitive Abilities

3.1 Introduction

In a context within which extending working life is a priority in the UK policy agenda, with the state pension age (SPA) gradually rising to 67 and potentially 68 for men and women (Department for Work and Pension 2013), a study of the consequences of retirement on cognitive capital is relevant for at least three reasons. First, there is an association between the process of accumulation and deterioration of human capital with that of cognitive capital (Rohwedder and Willis, 2010). Studying the extent to which retirement affects the deterioration of cognitive capital is therefore important in order to understand and potentially contrast human capital depreciation during various phases of old age (Mazzonna and Peracchi, 2012). Second, there is evidence that cognitive abilities, in particular numeracy, are strongly related to financial literacy. Although causation is still under debate, the relevance of this relationship is enhanced by a context in which social provisions shrink and private pensions and savings become increasingly important sources of income for the elderly (Banks and Oldfield, 2007). Third, cognitive measures are shown to be significantly correlated with health outcomes. Reviewing previous studies, Deary (2012) reports that cognitive capital is inversely associated with different causes of mortality such as cardiovascular disease, suicide, homicide and accidents, while Salthouse (2012) highlights a significant association between cognitive functioning and the ability of elderly people to live independently, experiencing a lower risk of depression and facing better general health.

In this paper we analyse the extent to which retirement influences the cognitive performances of older workers in Britain, and explore the existence of heterogeneous effects across gender, education level and job type. The analysis makes use of data from Wave 3 of Understanding Society and, following the approach proposed by Mazzonna and Peracchi (2012), estimates the relationship between time spent in retirement and cognitive decline using an Instrumental

Variable (IV) approach. The contribution of this paper to the limited UK-based literature is twofold. First, we employ a novel dataset in an area of research which mainly uses data from the English Longitudinal Study of Ageing (ELSA). Second, we add to existing UK evidence by analysing men and women separately and exploring the heterogeneity of the retirement-induced cognitive decline across various levels of education and type of work performed.

We find that retirement worsens cognitive decline for both men and women, although the estimated coefficients indicate smaller effects among females. In particular, depending on the cognitive measure analysed, an extra year in retirement is predicted to generate a decline of between 0.035 and 0.089 of a standard deviation for men and between 0.015 and 0.048 for women. We also find that, among the latter, those employed in routine occupations face a lower retirement-induced cognitive decline and could potentially benefit from it.

Given that postponing retirement is predicted to be potentially beneficial for the cognitive capital of older workers, our results advocate the importance of keeping an active and mentally stimulating lifestyle following retirement.

This paper is organised as follows. Section 3.2 discusses the theoretical background and reviews a number of relevant studies on the relationship between retirement and cognitive decline. Section 3.3 briefly introduces the UK system of public support for older people. Data and methodology are described in Section 3.4. In Section 3.5 we report the results of our analysis and carry out robustness checks. Conclusions follow.

3.2 Background and review of the literature

According to the model proposed by Cattell and Horn (Horn and Cattell, 1966), what is commonly known as general intelligence can be considered to be the result of the interaction of different factors. Among these factors, fluid intelligence and crystallised intelligence are the main ones. Fluid intelligence is the ability to deal logically with new and/or unfamiliar situations. It usually involves processes of abstraction, categorization and placing objects/events in relation to one another. Fluid intelligence is assumed to work independently from previously held knowledge. Crystallised intelligence is the ability to employ previously acquired knowledge and experiences and it is relevant for tasks such as those involving vocabulary (Gustafsson, 1984; Salthouse, 2010; Horn and Cattell, 1966).

Although ageing is correlated with cognitive decline, a consensus exists in the psychology literature on different cognitive functions evolving heterogeneously with age. In particular, Salthouse (2010) shows that the decline of cognitive functions related to fluid intelligence starts in early adulthood, while crystallised intelligence tends to increase well into adulthood and begins to decline after the age of 60.

Rohwedder and Willis (2010) develop a parallelism between the process of the development of human capital as modelled by Ben-Porath (1967) and the development of fluid and crystallised intelligence over time. In particular, the authors argue that the main inputs of the human capital production function, which are ability, current stock of human capital, and other purchased inputs, can be seen, respectively, as fluid intelligence, crystallised intelligence, and involvement in activities which facilitate human capital formation such as schooling and on-the-job training. In this context, the stock of human capital evolves according to the rates of investment and depreciation of human capital, where the latter can be interpreted as losing crystallised knowledge. Investments in human capital formation and involvement in activities that stimulate cognitive processes are therefore expected to counterbalance the ageing related human capital depreciation.[26]

[26] See also Mazzonna and Peracchi (2012) for a formalised model of the formation of cognitive capital.

Within this framework, Rohwedder and Willis (2010) predict that retirement may negatively influence the process of depreciation of cognitive capital for two reasons. First, according to the "unengaged lifestyle" or "use it or lose it" hypothesis, retirement might provide a less cognitively stimulating environment than working, with the consequent worsening of the cognitive capital ageing profile. Second, if returns to work-related cognitive capital fall as retirement age approaches, it is also possible for workers to start reducing investments in cognitive capital while still working. The authors call this hypothesis "on the job retirement".

From an empirical point of view, the endogeneity of retirement decisions with respect to cognitive performances represents the main challenge for the identification of the causal effect of retirement on cognitive abilities. The issue is often solved using retirement eligibility rules as instruments for the retirement decision. A number of papers have applied this strategy to pooled cross-country data, relying on cross-country variations in early and standard retirement age to address the endogeneity. The results are mixed, with evidence in favour of both negative and non-significant effects of retirement on cognitive performance (Rohwedder and Willis, 2010; Mazzonna and Peracchi, 2012; Mazzonna and Peracchi, 2014; Coe and Zamarro, 2011).

Rohwedder and Willis (2010) pool 2004 data from the Survey of Health, Ageing and Retirement in Europe (SHARE) which contains data from 11 EU countries[27]; the US Health and Retirement Survey (HRS); and the English Longitudinal Study of Ageing (ELSA). They find evidence that retirement negatively impacts cognitive abilities measured as the combined result of an immediate and delayed word recall test. Using the same SHARE data, Mazzonna and Peracchi (2012) employ a similar identification strategy although retirement is now allowed to change the slope of the cognitive capital age profile rather than shifting it. While in Rohwedder and Willis (2010) retirement enters the analysis as a binary indicator variable, which implies that retirement

[27] Austria, Belgium, Denmark, France, Germany, Greece, Italy, Netherlands, Spain, Sweden and Switzerland.

generates a shift in the age profile of cognitive decline, in Mazzonna and Peracchi (2012) a continuous measure of time since retirement is used as an endogenous regressor and time elapsed since eligibility for early and standard pensions as instrumental variables. Moreover, the study conducts separated analysis by gender and uses five different measures of cognitive abilities. The authors show evidence that retirement worsens the rate of decline of cognitive capital, although the effects are heterogeneous across gender. The authors also find that the level of education influences cognitive performances at older ages and that low educated women tend to experience a stronger decline in cognitive performance after retirement than more highly educated women. Mazzonna and Peracchi (2014) extend their previous analysis by modelling the effect of retirement both as a binary treatment and as a slope effect and, exploiting the longitudinal dimension of SHARE, by estimating a first difference instrumental variable model. The results confirm the existence of a negative effect of retirement on cognitive decline, while a beneficial immediate effect of retirement is identified only for manual workers. By contrast, using 2004 SHARE data, and focusing on men only, Coe and Zamarro (2011) find evidence of retirement improving general health but not cognitive measures, measured by immediate and delayed recall tests and a verbal fluency test.

However, as reported in Bonsang et al. (2012), country specific cultural and institutional characteristics are likely to influence both the age profile of cognitive abilities and the settings governing retirement rules. The authors report that citizens from northern countries tend to perform better than their southern counterparts in various health outcomes and that they face higher retirement ages. If differences in the eligibility ages for retirement failed to explain such patterns across countries then the exclusion restrictions would be invalid and the effects of retirement on cognitive abilities over-estimated. In this sense, although the use of country-fixed effects is likely to mitigate the problem, single country studies are likely to be more suitable than cross-country ones for this kind of analysis.

US-based evidence provides mixed results. On the one hand, using HRS data, Coe et al. (2012) show a limited impact of retirement on cognitive outcomes, and highlight the heterogeneity of such effects between typologies of workers. In particular, the authors show that the cognitive performances of white collars are not significantly affected by retirement once the endogeneity of retirement decision is accounted for, while retirement emerges to be positive for blue collar workers. Within the "use it or lose it" hypothesis, the authors interpret the finding as blue collar workers being able to access more cognitively stimulating activities during retirement than whilst still working, while white collars do not experience a significant reduction in the exposure to such activities. On the other hand, basing their analysis on a panel dataset of American respondents to the HRS, Bonsang et al. (2012) estimate a fixed effect model with instrumental variables, where the issue of endogeneity of retirement decisions is accounted for by using two indicator variables for having reached the age of 62 and of 65 as instruments. The authors account for a delayed effect of retirement on cognitive abilities by defining the endogenous independent variable as being retired for at least one year, and in different specifications also use time since retirement as endogenous variable, and time since the age 62/65 thresholds as instruments. The analysis shows evidence in favour of a worsening of the age profile of cognitive measures after retirement.

UK-based studies suggest the presence of negative effects of retirement on cognitive measures, although the evidence is quite limited. Adam et al. (2007) apply a stochastic frontier approach for 2004 data from ELSA for the UK, HRS for the US and SHARE, separately. The results indicate a worsening in cognitive efficiency with time spent in retirement. Behncke (2012) applies non parametrical IV and matching techniques to ELSA data in order to analyse the health effects of retirement. Modelling retirement effects as discrete shifts, the author finds evidence that retirement increases the probability of experiencing a cognitive functioning problem measured through the word recall test and awareness of current date.[28]

Using data from Understanding Society, this paper analyses the role of retirement in influencing the cognitive performances of older workers in Britain. Additionally, we explore the existence of heterogeneous effects across gender, education level and job type. Following Mazzonna and Peracchi (2012), we adopt an IV approach and use time elapsed since state pension age as instrumental variable for the time spent in retirement. The next section briefly describes the functioning and evolution of the system of public support for older people in the UK.

3.3 Retirement age and state pension age in the UK

State pension age is the age at which the basic state pension and a number of other benefits become available for older people. Introduced in 1946 and effective from 1948, the UK basic state pension has been designed as a flat rate benefit aimed at providing a basic level of resources to pensioners. Eligibility is based on both age and contribution history, with female state pension age (SPA) originally set at 60 and male SPA at 65. Earnings-related pensions, flat rate non-contributory benefits and a number of means-tested benefits complete the public system of support for pensioners.

A process of reform of the system of public support of elderly people is ongoing. Over the years, budgetary considerations have not only prevented the full development of earnings related pensions, but also eroded the capacity of the basic state pension to guarantee minimum subsistence levels to all pensioners, with the consequent increase of the relevance of means-tested benefits aimed at older people. Current reforms, such as the phasing in of the New State

[28]Focusing on different health outcomes, Johnston and Lee (2009) apply a regression discontinuity analysis around age 65 to a pooled data of the 1997-2005 Health Survey for England (HSE). The authors find evidence that retirement has a beneficial effect on mental health, measured by the GHQ-12 questionnaire.

Pension in April 2016, aim at re-establishing the Beveridgean nature of the state pension system (see Bozio et al., 2010 for further details on the development of the public system of support for pensioners).

The process of reform has also involved an increase in the state pension age. In particular, under the provisions of the 1995 Pension Act, female state pension age is currently increasing from 60 to 63 years of age. Women born between 6th April and 5th May 1950 have been the first to be affected by the reform, reaching eligibility on the 6th May 2010, with the state pension age spanning from 60 years and a day to 60 years and a month. Women born on each following month have faced a further one month increase in the state pension age, until a state pension age of 63 is reached by women born between 6th March and 5th April 1953 who gained eligibility on 6th March 2016. Under the provision of the 2011 Pension Act, female state pension age will increase faster for those born after the 6th April 1953, until catching-up with male state pension age of 65. The state pension age for men and women is then due to reach 66 for those born between 6th October 1954 and 5th April 1950, and to further increase to 67 under the Pension Act 2014, and to the age of 68 under the 2007 Pension Act (Department for Work and Pension 2013). Figure 3.1 shows the evolution of state pension ages over time.

It should be noted that no compulsory retirement is attached to the state pension age. Although until 2006 employers had the possibility to set retirement ages for their employees, the adoption of a Framework Directive of the European Commission led to the 2006 Employment Equality (Age) Regulations, which prohibited any unjustified direct and indirect age discrimination. As a consequence, employers lost their ability to set retirement ages for their employees below a default retirement age of 65, except if objectively justified. Different from a compulsory retirement age, workers could work past the default retirement age if in agreement with the employer. The default retirement age was abolished in 2011, prohibiting employers from forcing employees into retirement on the ground of age, although this included the provision of objectively justified exceptions (Pyper, 2013).

State pension age is, hence, the age at which state retirement benefits become available and traditionally represents the age at which an important part of the labour force enters retirement (Bound and Waidmann, 2007). In our analysis we use state pension age as an instrumental variable for retirement decisions, and its relevance is further discussed in Section 3.4.3.

3.4 Data and methods

3.4.1 Data and descriptive statistics

In this paper we analyse the extent to which retirement influences cognitive decline in the UK. The analysis makes use of Wave 3 data from Understanding Society, the UK Household Longitudinal Study (UKHLS)[29]. Starting in January 2009, Understanding Society is a large household panel survey which annually re-interviews adult (16 and older) and young (10-15) household members, collecting information on a great variety of household and individual circumstances and on their evolution over time. The General Population Sample (GPS) used in this analysis is based on a proportionally stratified clustered sample of addresses for England, Scotland and Wales and on a systematic, unclustered, random sample of addresses for Northern Ireland. The GPS sample contained just over 26 thousand households in wave 1, with above 43 thousand individuals giving full or proxy interviews.

A cognitive ability module was issued in the third wave of Understanding Society. The module contains a number of cognitive tests administered consistently with other surveys such as the English Longitudinal Survey of Aging (ELSA). Wave 3 fieldwork spanned from January 2011 to July 2013, with a household response rate of 75.3 percent in Great Britain and 79.1 percent in

[29] University of Essex. Institute for Social and Economic Research, NatCen Social Research. (2014b).

Northern Ireland and more than 33 thousand adult individuals with a full or a proxy interviews (see Knies, 2014 for further details).

Despite the cross-sectional nature of the data used in this paper might represent a potential limitation, the use of data from Understanding Society is one of the novelties of this work in an area of research in which the scarce UK-based evidence is mainly based on data from ELSA. Although the panel dimension is available in ELSA, it should be noted that the use of panel data in this field of research is complicated by evidence on a positive learning effects when the same test is administered to the same individuals over time (Mazzonna and Peracchi 2012).

In our estimation sample we include fully respondent individuals aged between 50 and 70 (both included) reporting to have ever worked and to be either active in the labour market or retired.[30] We exclude unusually early retired individuals by dropping those whose retirement started before the age of 50. Labour market status is defined by combining the information on whether the respondent was in work or temporarily out of work in the week before the interview and that on the self-reported current labour market status. Any respondent with a contradictory status is excluded from the estimation sample. We also exclude from our sample individuals whose retirement date is either missing or inconsistent with the information on labour market status provided in previous waves, or those who have missing values on any of the variables used in the analysis.

Panel A of Table 3.1 summarises the characteristics of the resulting sample. The average age is close to 60, with retired averaging 66-years-old and non-retired 57-years-old, respectively. Males account for 47 percent of our estimation sample, while about one third of our respondents are retired. The proportion of retired respondents is slightly higher among females than males, arguably because females are subject to a lower state pension age. Years since retirement and

[30] As a robustness check we extended the sample by including people up to the age of 80, see Section 3.5.3.

years since the state pension age measure the number of years elapsed since retirement occurred or the state pension age was reached. Both variables are originally measured in months and divided by 12. The variables take value of 0 if respondents are respectively non retired or younger than the state pension age. Data from annual history questions in Waves 1 to 3 are used to retrieve information on the retirement age.[31]

One quarter of our sample is low qualified, measured as having no-qualifications or other qualification as opposed to highly qualified respondents, defined as those with GCSEs or above. Such proportions are similar across genders but not across retirement statuses, with 36 percent of retired people reporting to be low qualified as opposed to 23 percent of non-retired respondents. Controlling for heterogeneity in cognitive decline with respect to education might be important as Mazzonna and Peracchi (2012) show evidence of less educated women experiencing a stronger decline than the rest of their sample.

The proportion of individuals performing, or who performed in the last job, a routine task is 11 percent. The Job National Statistics Socio-economic Classification (NS-SEC) is used to classify a job as "routine" as opposite to non-routine. While the proportion of people employed in routine jobs is constant across retirement statuses, a higher proportion of males enter in this category compared to females – 14 percent versus 9 percent, respectively. Occupation type is shown to affect retirement induced cognitive decline, with Coe et al. (2012) reporting evidence of

[31] The date on which the respondent left their last job is used to measure retirement for respondents who were interviewed for the first time in wave 2 or wave 3 of Understanding Society. Also, being the day of birth not available and day of retirement either not available if someone retired before wave 1 or often missing if someone retired after that we choose to measure both variables in months. Finally, as explained in section 3.3, reforms in state pension age are implemented according to the date of birth, with cut-off points set on the 6th day of each month. Being the day of birth not available we apply state pension age rules relative to those born between, say, 6th April and 6th May of a given year to all those born in April of that year, while those born between 1st and 5th May of that year will follow state pension age rules related to those born between 6th May and 5th June. Consequently, if rules state that respondents become eligible on the 6th day of a given month, we apply that month as the one in which state pension age is reached. These assumptions, which are entirely data driven, are equivalent to implying that all women born in April 1950 will reach state pension age at the age of 60 and one month; those born in May 1950 will reach state pension age at the age of 60 and two months, and so on. Being the misclassification driven by the day of birth in a given month, we can assume this to be random and hence not biasing our estimates. Moreover, the consequences of misclassification should not be relevant in size, as the differences in state pension age for people born in consecutive months are usually contained to one or two months.

heterogeneity between blue collar and white collar workers in the US, and Mazzonna and Peracchi (2014) showing that cognitive decline affect workers from manual occupations differently.[32]

Three quarters of our sample live with a partner, with a higher prevalence among males than females (81 percent versus 71 percent). Living with a partner is expected to mitigate cognitive decline as it could arguably encourage individuals to maintain active cognitive functioning (Mazzuco et al. 2013). 81 percent of our sample reports to be in good general health although the prevalence is higher among non-retired than retired individuals (83 percent versus 77 percent). If, on the one hand, general health is likely to suffer endogeneity issues, its introduction might help in disentangling the role of age related health decline. Finally, Table 3.1 also contains the proportion of respondents living in each of the countries of the UK. Specifically, 83 percent of the respondents live in England, 8 percent in Scotland, while the rests are equally split between Wales and Northern Ireland.

Following Mazzonna and Peracchi (2012), we use four measures of cognitive ability throughout our analysis. (i) Immediate recall and (ii) delayed recall tests measure the number of correct answers to a test consisting of a computer reading a list of 10 words and the respondent having to remember as many of them as possible. While in the immediate recall test the respondent is asked to lists the words immediately after hearing them, in the delayed recall test the respondent is asked to do so after other cognitive tests have been performed. Both immediate and delayed recall tests are expected to assess episodic memory. (iii) Numeric ability is assessed by a test requiring the respondent to perform some simple numerical operations related to the use of numbers in everyday life. In particular, a set of three questions is submitted to all respondents. In the event that the respondent makes one or more mistakes in answering these three questions, an

[32] Including the workers employed in semi-routine occupations in the routine category does not significantly affect the results of the paper. Results are available on demand from the author.

extra question is asked in a second round. If the respondent gives three correct answers, a fourth and eventually a fifth question are asked. We use the number of correct answers to measure numeric ability. This measure is expected to be related to wealth and financial literacy. (iv) Verbal fluency is measured by the number of correct answers in a test consisting of respondents naming as many animals as possible in one minute. Verbal fluency measures aspects of executive functioning, and it requires mental flexibility, organization and abstract abilities (see McFall, 2013 and papers cited therein).

Panel B of Table 3.1 shows that male respondents perform better than females in numeric ability (3.99 versus 3.54 in raw scores) and, to a lesser extent, in verbal fluency (22.50 versus 22.18 in raw scores). By contrast, females outperform males in both immediate and delayed recall, with a raw score of 6.40 versus 6.10, and 5.32 versus 4.90, respectively. Important differences also emerge when we compare cognitive performances of retired and non-retired respondents, with the latter outperforming retired people in all the cognitive tests considered.

Figure 3.2 shows the presence of a negative age profile in cognitive measures, with gender differences holding across the age distribution. A negative relationship also emerges by plotting cognitive performances against years spent in retirement (Figure 3.3).

Since years in retirement is positively correlated with age, this evidence is expected. Similarly to Mazzonna and Peracchi (2012), we therefore further investigate the relationship between age, retirement, and cognitive performance by differentiating the age-profile of the cognitive tests between retired and non-retired individuals. For both males (Figure 3.4) and females (Figure 3.5), we observe that at later ages retired individuals tend to perform worse than non-retired ones, whilst the opposite is true at earlier ages. In particular, whilst for men the cut-off point is close to the age of 65, for women this happens at approximately 60 years of age, with the exception of numeric ability. This evidence suggests that people who are already retired at ages below the state pension age outperform those of a similar age who are active in the labour market, whilst the opposite applies to people who are above the SPA. Figure 3.6, where we plot the age profile of cognitive performances by retirement status and duration of retirement, confirms this finding.

The graphical evidence reveals that retired individuals experience a sharper decline in their cognitive scores over time than similarly aged people who are active in the labour market. This evidence is, however, partly in contrast with Mazzonna and Peracchi (2012) who show that retired people perform worse than working people across the age distribution. A positive selection into early retirement in the UK might entail better performances of early retired individuals compared with active individuals of a similar age. Supportive evidence is provided in Table 3.2 where we summarise individual characteristics and test performances by gender, retirement status, and whether the respondent is above or below the state pension age. For both males and females it emerges that individuals who are retired and below the SPA perform better than any other group in all the cognitive measures, showing also the lowest prevalence of low qualification and routine jobs. In the UK, early-retirement therefore appears to be a status in which better off people tend to select. The finding is consistent with Blundell et al. (2002), who show how the incentives embedded in occupational pensions increase the probability that eligible people retire earlier than the state pension age. The positive selection into early retirement is likely to introduce an attenuation bias in our naïve OLS estimates since intuitively early retirees have a positive number of months in retirement and score highly in cognitive measures.

Although the descriptive evidence is consistent with the existence of a cognitive decline induced by retirement, the phenomenon could also be driven by reverse causality issues – people retire when cognitive abilities decline. Furthermore, another driver could be the correlation between retirement and ageing – retired individuals are, on average, older than non-retired individuals and have therefore experienced a greater cognitive decline. In the remainder of the analysis we employ an instrumental variable approach to mitigate the confounding effects described above and to identify the causal effect of retirement on cognitive performances.

3.4.2 Identification strategy

In this paper, we study how retirement influences cognitive decline in the UK. The endogeneity of retirement with respect to cognitive decline represents the main identification issue in determining the causal effect of retirement on cognitive capital. Whilst retirement can influence the cognitive decline through "use it or lose it" or "on the job retirement" arguments (Rohwedder and Willis, 2010), it is also possible for people who experience cognitive decline to be pushed into retirement. Consistent with previous literature, we employ eligibility rules for state pension age as an instrument for retirement decisions (e.g., Rohwedder and Willis, 2010; Mazzonna and Peracchi, 2012; Coe and Zamarro, 2011).

First, following Mazzonna and Peracchi (2012) in particular, for each cognitive measure used we estimate an OLS regression of the form described in equation (1):

$$C_i = \beta_0 + \beta_1\, Age_i + \beta_2\, RetY_i + X_i'\,\gamma + \varepsilon_i \qquad i = 1, \dots, N \tag{1}$$

where C_i measures the standardised test score for the individual i, Age_i is the age at the time of the interview, $RetY_i$ measures the number of years elapsed since retirement and X_i is a vector of individual characteristics. Years spent in retirement are set to 0 if the respondent is not yet retired, such that $RetY_i = max(0, Age_i - RetAge_i)$. Both age and years since retirement are originally measured in months and divided by 12. We estimate different sets of regressions for men and women.

Second, since the OLS estimates are likely to suffer from the endogeneity of retirement with respect to cognitive decline, we then use the time elapsed since state pension age as an instrumental variable for years spent in retirement. In particular we define the instrument as

$$SpaY_i = max(0, Age_i - SPA_i) \tag{2}$$

where SPA_i captures the state pension age of the i-th individual. While the coefficient on age (β_1) is expected to capture the age-related cognitive decline in the absence of retirement, the coefficient on years since retirement (β_2) – instrumented by years elapsed since SPA – measures the additional cognitive decline which is imputable to retirement. Given the positive selection into early retirement observed in our data, we expect the OLS estimates to be affected by attenuation bias, and, hence, for the coefficient on years since retirement estimated using OLS to be smaller in size (less negative) than the one estimated using IV. [33]

Following previous literature (Mazzonna and Peracchi, 2014), our identification strategy assumes linearity of age-related cognitive decline. This is a reasonable assumption given the age range in our analysis, 50 to 70 years, and results from previous studies (Coe and Zamarro, 2011). However, we perform robustness checks of the linearity assumption in Section 3.5.3.

3.4.3 Instrument validity

As previously mentioned, we deal with the potential endogeneity of retirement using the time elapsed since the state pension age as an instrument.

[33] Our interest lies in analysing the extent to which retirement determines changes in age-related cognitive decline. A pure regression discontinuity approach which compares individuals who are just above or just below the state pension age threshold is therefore not informative in our setting. A different approach could consist in exploiting the increase in SPA for women and, hence, comparing two women of the same age with different elapsed time periods since SPA. Given the cross sectional nature of our dataset and that the SPA reform maps age, this could only be done by exploiting the fact that wave 3 interviews spanned over two years. Hence, it is possible for some women born in two consecutive years to report the same age at the date of interview and different elapsed time since SPA if affected by the reform. The number of women falling into this category is, however, small and, given the smooth implementation of the SPA increase, the differences in time elapsed since SPA only amounts to a few months. Moreover, all the women affected by the reform in our data are recently retired. We therefore considered the IV approach the most suitable for our analysis.

State pension ages are currently being reformed in the UK for both men and women according to the description provided in Section 3.3. Since the data used in this analysis is collected between 2011 and 2013, no men in our sample actually reached state pension age with the modified rules yet. Only men born since December 1953 are in fact affected by the increase in SPA, with the first cohort reaching SPA in March 2019. Hence, although men who will retire with an increased SPA are part of our sample, our identification strategy for men relies on the changes in retirement probabilities before and after the age of 65, on the grounds that nothing else specifically related to cognitive decline happens at that age (Johnston and Lee, 2009).

Among all women, 60 percent are born on or after April 1950 and are therefore affected by the reform. Among those affected by the reform, close to 13 percent - and just below 8 percent of all women in our sample – are over the age of 60 but face a higher state pension age. These women would have already reached the state pension age if the reform was not in place but, instead, they either have not reached it yet or reached it with some delay. Hence, although limited, our analysis includes variations in the state pension age for women.

Figures 3.7 and 3.8 graphically assess the validity of our instrument, confirming that the state pension age is a suitable instrument for retirement decisions. In particular, Figure 3.7 reports the distribution of retirement age for individuals who are retired at the time of the interview. The chart includes both the probability density function (p.d.f.) and the cumulative density function (c.d.f.) for males and females separately. While the former describes the proportion of retired individuals who retired at each point of the age distribution, the latter shows the proportion of retired individuals who retired by a certain age. Both in terms of c.d.f. and p.d.f., the figures show discontinuities at the age of 65 for males, with 20 percent retiring at this age, and at the age of 60 for females, with 25 percent retiring at this age. In both cases there is a strong correspondence between retirement age and state pension age. In Figure 3.8 we report a local polynomial fit of being retired on age. For both men and women, the fit is performed separately for people who are above and below their state pension age. The chart shows the presence of a discontinuity of between 0.2 and 0.3 in what can be interpreted as the probability of being retired in correspondence to the relevant state pension age. In the next section we report the first-stage estimates to support this evidence.[34]

3.5 Results

3.5.1 Baseline

In Table 3.3 we report OLS estimates for our baseline model specification, where the dependent variables are the standardised test scores and the independent variables of interest are (i) age, and (ii) years spent in retirement. We also control for the individual characteristics described in the previous section. The estimates should be treated as naïve because of the endogeneity issues discussed in previous sections. Consistent with previous findings and theoretical considerations, estimates show a negative relationship between age and three out of the four cognitive measures analysed.[35] Numeric ability represents the exception, showing a positive association with age for both men and women. Arguably, these positive correlations may be the consequence of a cohort-effect for which we cannot control given the cross-sectional nature of the data (Schaie et al., 2004). In contrast with Mazzonna and Peracchi (2012), after having controlled for age, the naïve OLS results do not show any significant effect of years since retirement on cognitive measures.

Amongst other regressors, having low academic qualifications and having performed a routine job are associated with a worse performance in the cognitive tests, while having a partner is associated with better outcomes for males at the immediate word recall test and for both males and females at the numeric ability and verbal fluency tests. As expected, good general health is

[34] A graphical inspection reveals similar discontinuities in correspondence of the SPA if we only focus our analysis on people who reached state pension age from 2006 onwards.
[35] The variable age has been modified such that a value of 0 indicates age 50, the minimum value in our sample.

related to a better cognitive performance, although the relationship is possibly endogenous as general health is likely to be correlated with retirement decisions and with cognitive measures. Country dummies are sometimes statistically significant, in particular living in Wales is associated with lower cognitive scores, arguably because of language related issues.

In Table 3.4 we report the first stage estimate of the IV. The table shows that the number of years elapsed since state pension age is a valid instrument for years spent in retirement. The coefficient on the variable of interest is, in fact, positive and highly statistically significant, indicating that a one extra year since state pension age has been reached is associated with a 9 months increase in time since retirement. For both males and females, the F-statistic is well above the conventional value of 10.

In Table 3.5 we report the IV estimates of our base model, where years elapsed since state pension age is used as an instrumental variable for years spent in retirement. First, the coefficient on age loses statistical significance in most of the regressions but remains positive and relatively high in the regression for numeric ability for both men and women. Although puzzling, this result can be explained by the fact that the cognitive functions belonging to the broad category of crystallised intelligence tend to improve until adulthood and only start to decline from the age of 60 (Salthouse, 2010).

The estimates show a negative and statistically significant effect of years since retirement on all the cognitive measures, with the exception of verbal fluency for females, where the effect is negative but insignificant. An increase in time spent in retirement is therefore predicted to negatively affect cognitive development both for males and females. The size of the effect varies across genders and cognitive measures, with an extra year of retirement associated with a decline of between 0.035 and 0.089 of a standard deviation for males, and between 0.015 and 0.048 of a standard deviation for females. These results are consistent with previous findings and with the prediction of the “use it or lose it” argument (Bonsang et al., 2012; Mazzonna and Peracchi, 2012; Rohwedder and Willis, 2010).

With respect to other regressors, the estimated coefficients are in line with the OLS estimates reported in Table 3.3. The results of the reduced form model are reported in Table 3.6 and are highly consistent with the IV estimates.

Hence, we find evidence that retirement negatively influences cognitive decline, with the depreciation rate of cognitive capital for retired individuals being higher than for working individuals. In the next subsection we explore the heterogeneity of such a decline with respect to education and type of job performed.

3.5.2 Heterogeneity in cognitive decline: the role of education and job type

In this sub-section we extend our baseline analysis by studying whether retirement affects the cognitive decline of various groups of respondents differently from one another. In particular, following Mazzonna and Peracchi (2012) we first study whether retirement related cognitive decline differs between low qualified individuals and the rest of the population. Second, in the spirit of Coe et al. (2012) and Mazzonna and Peracchi (2014), we analyse heterogeneity in retirement-induced cognitive decline between routine and non-routine workers. It should be noted that in our estimation sample the proportion of low qualified individuals is similar across genders (26 percent for men and 28 percent for women), while considerable differences arise with respect to performing routine occupations as 14 percent of men fall into this category as opposed to 9 percent of women.

Table 3.7 and Table 3.8 show the results after modifying our baseline specification by adding interaction terms between the low qualifications dummy variable and both age and years since retirement. The first stage regressions are reported in Table 3.7 and second stage IV estimates are reported in Table 3.8. Our results do not show evidence of heterogeneity in retirement-induced cognitive decline across levels of education as none of the interaction terms between being lowly qualified and years since retirement are statistically significant.[36] These results are in contrast to Mazzonna and Peracchi (2012) who find evidence that low educated women face a steeper cognitive decline than highly educated ones.

Coe et al. (2012) explore whether heterogeneity in retirement-induced cognitive decline arises between blue and white collar workers in the United States, The authors find no evidence of retirement-induced cognitive decline for white collars workers, while the cognitive abilities of blue collar workers tends to improve following retirement. Consistently, Mazzonna and Peracchi (2014) find evidence of a relevant, immediate positive effect of retirement on the cognitive performances of the workers employed in physically demanding occupations. Our evidence, reported in Tables 3.9 and 3.10, shows no significant differences in the effect of retirement on cognitive decline between men with routine jobs and the rest of the male population. However, we find evidence of women who had routine jobs experiencing a less steep cognitive decline after retirement than the rest of the female population. Analysing the size of the interaction coefficient, the cognitive measures of women from routine job could, in fact, benefit from retirement. This result is partly consistent with the findings of Coe et al. (2012) and Mazzonna and Peracchi (2014) and, within the “use it or lose it” interpretation of retirement-induced cognitive decline, it can be explained with routine workers suffering less, or even benefiting, as a result of the changes to cognitive engagement associated with retirement.

3.5.3 Robustness checks

In this section we discuss a number of checks to verify the robustness of our results.

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[36] In different specifications we have modified our model by including GCSE and equivalent in the low qualification category as well as by replacing the low qualification category with being highly qualified, i.e. having a degree or more. In both cases the results are highly consistent with those here reported.

First, we test the fit of different placebo models in which cognitive decline is assumed to start either before or after the official retirement age. We do so with the aim of showing whether the base model presented in the previous section provides the best fit for the data. Since the variable measuring years since retirement is left censored, this means that we cannot observe when the non-retired individuals will actually retire. Thus, we are forced to perform these placebo tests using the reduced form model rather than the full IV specification.

An example may clarify this point. Say that a respondent is observed at age 64 and is not yet retired. For him/her the variable measuring the time elapsed since retirement would take a value of zero in our baseline specification. Suppose now that we want to test whether their retirement-induced cognitive decline starts before actual retirement, say 2 years before. If we knew that the respondent would retire at the age of 65, that is, in one year's time, then we could test whether his or her retirement-induced cognitive decline had started at the age of 63 and therefore assign a value of one year to the variable of interest. However, this would only be possible if we knew when non-retired respondents would actually retire. Since this information is not available to us, we circumvent the problem using the reduced form model, where we can easily modify the variable measuring the years elapsed since state pension age according to the hypothesis that we want to test. In the example above, we would test the fit of a model in which the variable of interests measures the time elapsed from two years prior the state pension age, i.e., since the age of 63 for men.

Table 3.A1 reports the Akaike's information criterion for our baseline specification and for different specifications in which cognitive decline is assumed to start from between 2 to 10 years prior to the state pension age. At each model specification we therefore modify our time "at risk" and assume a 2 year increase in the number of years passed since the start of the retirement-

induced cognitive decline. For each cognitive measure used, and for both males and females, the table shows that our baseline specification produces the best Akaike's criterion.[37]

In Table 3.A2 we repeat the exercises by assuming that cognitive decline starts from between 1 to 5 years after retirement (captured by the state pension age). Although it is possible to perform this test using IV, we choose to use the reduced form model for consistency and because it is possible to retrieve goodness of fit statistics using OLS. The results confirm that the baseline model is the one that best fits the data, with the only exception of the one year lead specification for males on the numeric ability and verbal fluency tests.

In the second robustness check, we repeat our IV estimates excluding from our analysis the individuals who entered retirement before state pension age was reached. In Table 3.2 we have already shown that individuals who retired early are a positively selected group and, although we already control both for level of education and job type, this might bias our estimates if unobserved characteristics make some individuals both more likely to be retired early, and hence have a positive number of years since retirement, and also to have better cognitive measures. Results reported in Table 3.A3 show that our findings hold if the early retired individuals are excluded from our estimation sample, with the exception of immediate word recall and delayed word recall for males. It should also be noted that coefficients on age gain statistical significance for most of the cognitive measures when the early retired are excluded from the estimation sample.

Third, we follow the modelling strategy of Mazzonna and Peracchi (2014) and estimate a model which controls for both the intercept and slope effects of retirement. The estimated model employs a binary variable for having passed the state pension age and the time elapsed since

[37] Used to compare the fit of models on the same data, the Akaike's Information Criterion (AIC) provides an index of the goodness of the fit and of the complexity of the model. Smaller values of AIC identify better models.

SPA as instrumental variables for the retirement indicator and the time elapsed since retirement. Table 3.A4 reports the IV estimates for males and females, while in Table 3.A5 we estimate the model separately for routine and non-routine workers but pooling together males and females for issues related to sample size. In both cases the results show no significant evidence of an intercept effect of retirement on cognitive capital. Table 3.A4 confirms the existence of the effect of retirement on cognitive decline, while Table 3.A5 shows that the effect is prevalent among workers employed in non-routine occupations. The pooling of data from men and women is likely to explain the differences between Tables 3.A4 and 3.A5, respectively, and Table 3.10.

Fourth, we estimate our baseline specification increasing the upper age-limit of our sample to 80. Although being more likely to be influenced by mortality bias, the results reported in Table 3.A6 confirm the main findings of our model. The estimated coefficients of interest for men are, however, smaller than those estimated using our baseline specification.

In Table 3.A7 we also report the estimates of our baseline specification after excluding general health from the list of controls included in the regression. Although the rationale for including it is to control for the effect of health conditions in cognitive decline, general health is likely to cause endogeneity problems in the data. We show that its exclusion does not significantly alter our estimates.

Finally, our identification strategy relies strongly on a linear functional form for the age-related cognitive decline. We therefore check the robustness of our results using different functional forms for age. In this regard, first, we test for a quadratic form and then redefine age as a categorical variable with 3-year bands. Table 3.A8 reports IV estimates for men, while Table 3.A9 reports these estimates for women. The bottom of each column reports the corresponding Akaike's criterion, estimated using the reduced form model. Column (1) reports the baseline estimate. The introduction of a quadratic age term (Column 2) results in an increase in the size of the estimated coefficients on years since retirement for men, where both age and quadratic age are statistically significant. Although not statistically significant, the introduction of the quadratic age term leads to a reduction in both the size and significance of the coefficients of interest. It should be noted however that for females both age and age squared are statistically non-significant and that for both males and females the introduction of the quadratic age worsens the model fit according to the Akaike's information criterion.

Controlling for age using 3-year age dummies (Column 3) results in an increase in the size of most of the coefficients of interest, while the Akaike's criterion based on the reduced form model continues to identify the linear age regression as the best one. Consistent with previous studies, and in agreement with the non-parametric profile of cognitive ability with respect to age and years of retirement which arises from a visual inspection of Figures 3.3 to 3.6, we therefore conclude that the linear age specification is the one which best fits the data.

3.6 Conclusions

In this paper we have analysed to what extent retirement affects cognitive abilities in Britain and our results indicate that retirement worsens age-related cognitive decline for both males and females.

The existing evidence on the relationship between retirement and cognitive functioning in the UK is scarce and its findings support the existence of a negative impact of ceasing working life on the cognitive capital of the individuals. Among the UK based studies, Adam et al. (2007) applies a stochastic frontier approach to 2004 data from ELSA and find evidence of a worsening in cognitive efficiency with time spent in retirement. Consistent findings are reported in Behncke (2012), who finds that retirement increases the chances of experiencing cognitive functioning problems. The analysis uses data from the first three waves ELSA and models the retirement effects as discrete shifts.

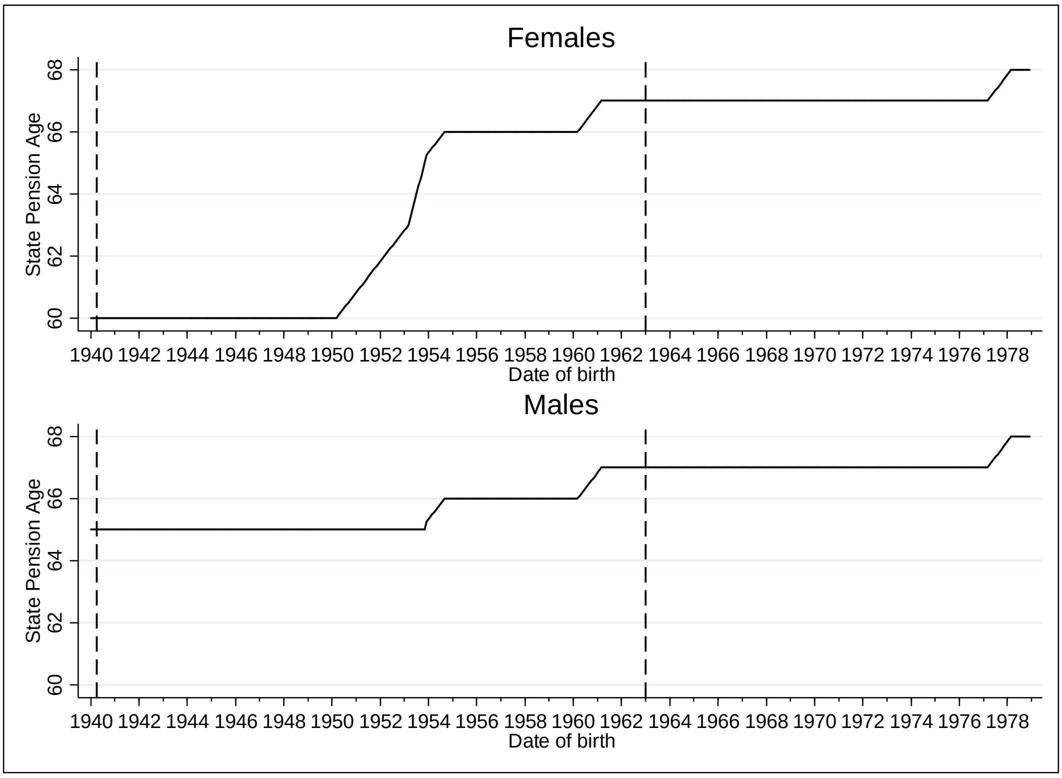
Our paper contributes to the existing UK based literature in various ways. First, following Mazzonna and Peracchi (2012), we model the effects of retirement as a factor which influence the slope of the cognitive decline process rather than causing a sharp shift. Second, we study males and females separately and explore the presence of heterogeneous retirement effects across levels of education and job types. Third, we do so by using data from Understanding Society, a novel dataset in an area of research predominantly based on data from ELSA.

Using four different measures of cognitive abilities, we find in particular that one year of retirement generates a decline in cognitive measures of between 0.035 and 0.089 of a standard deviation for men, and between 0.015 and 0.048 of a standard deviation for women. We have also found evidence of heterogeneity of response with respect to job type, with retirement-induced cognitive decline being significantly smaller, and potentially beneficial, for women who had routine jobs.

During a period in which extending the length of working life represents a priority in the UK policy agenda, our results indicate that postponing retirement could potentially have a positive effect on the cognitive capital of older workers, although women performing routine tasks will benefit less, or potentially suffer, from it. Focusing on cognitive capital only, it should be noted that our analysis leaves aside the effects of retirement on a number of other physical and mental health outcomes, which might well overturn the positive effect on cognitive capital identified here. Within the "use it or lose it" hypothesis, what should be emphasised is the importance of maintaining a healthy and cognitively engaging lifestyle following retirement from work as a way to maintain healthy cognitive functions.

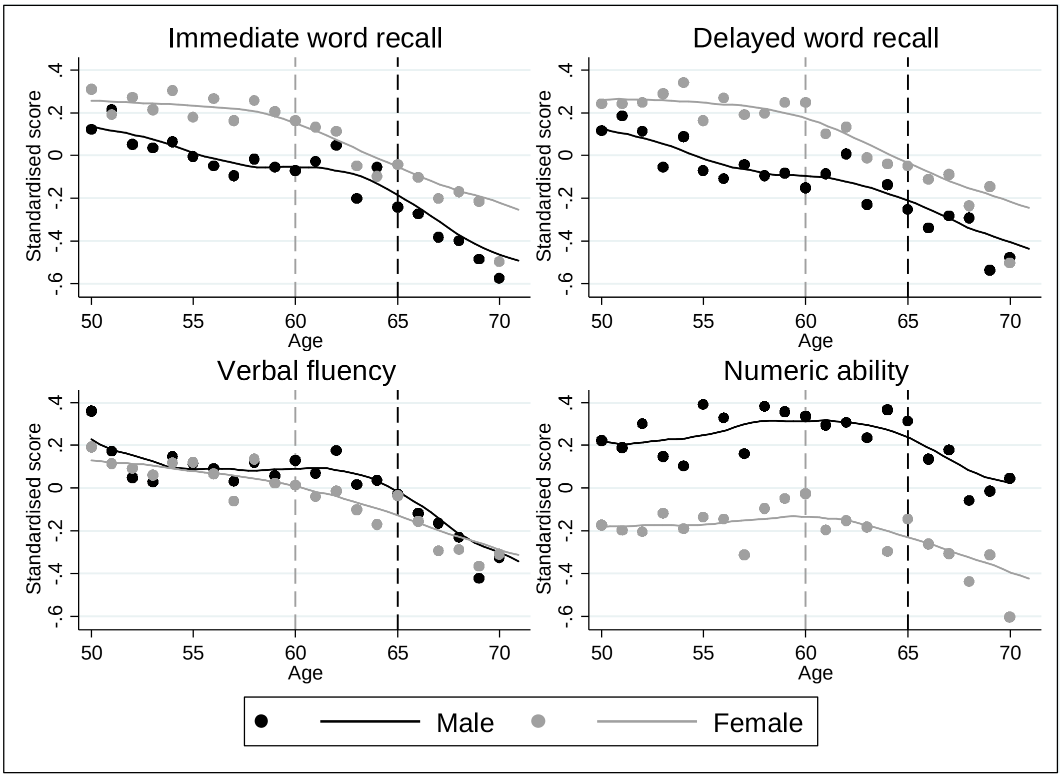
3.7 Tables and Figures

Figure 3.1: State pension age by date of birth



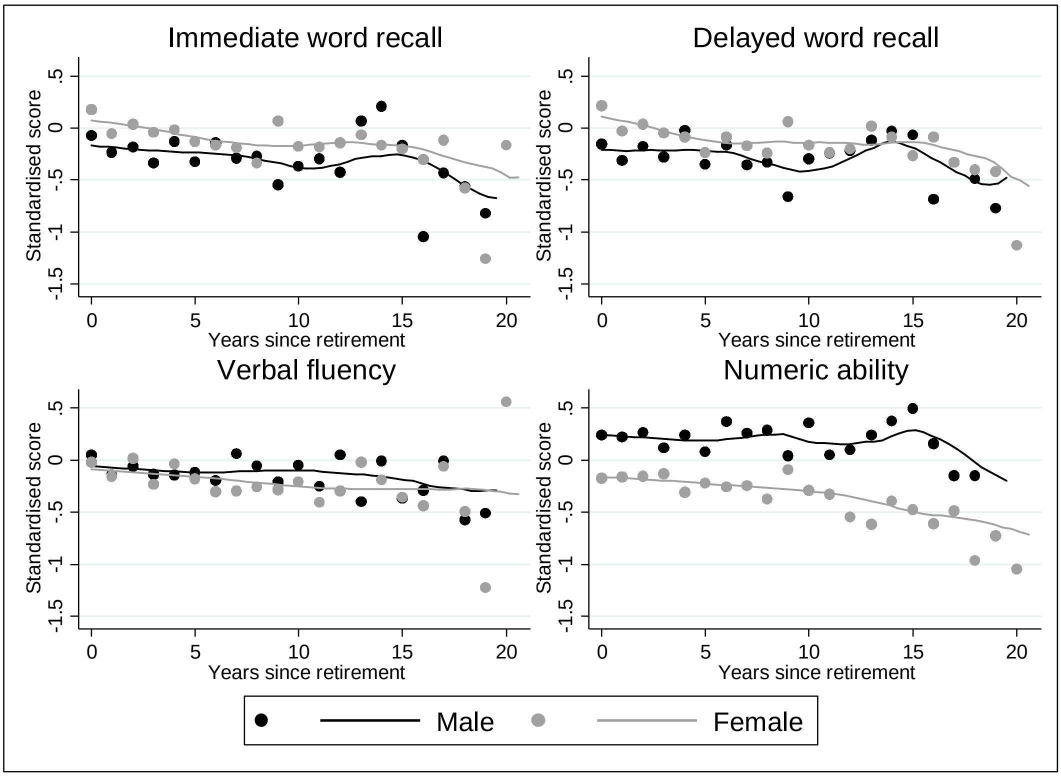
Note: Vertical lines identify the range of our estimation sample

Figure 3.2: Cognitive measures by age and gender



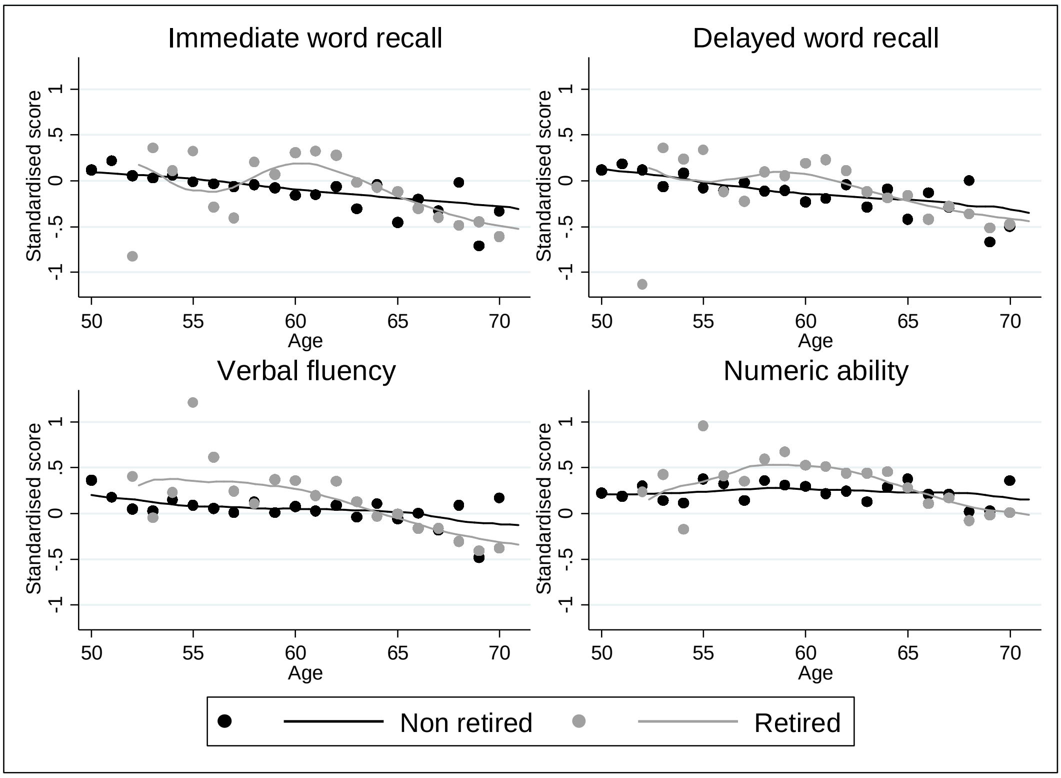
Note: the scatterplot identifies the age and gender specific averages computed by pooling observations in 1 year bands. The line is a local polynomial smoothed line fitted on actual observations. Vertical lines identify typical SPAs for males and females.

Figure 3.3: Cognitive measures of retired respondents by gender and years since retirement



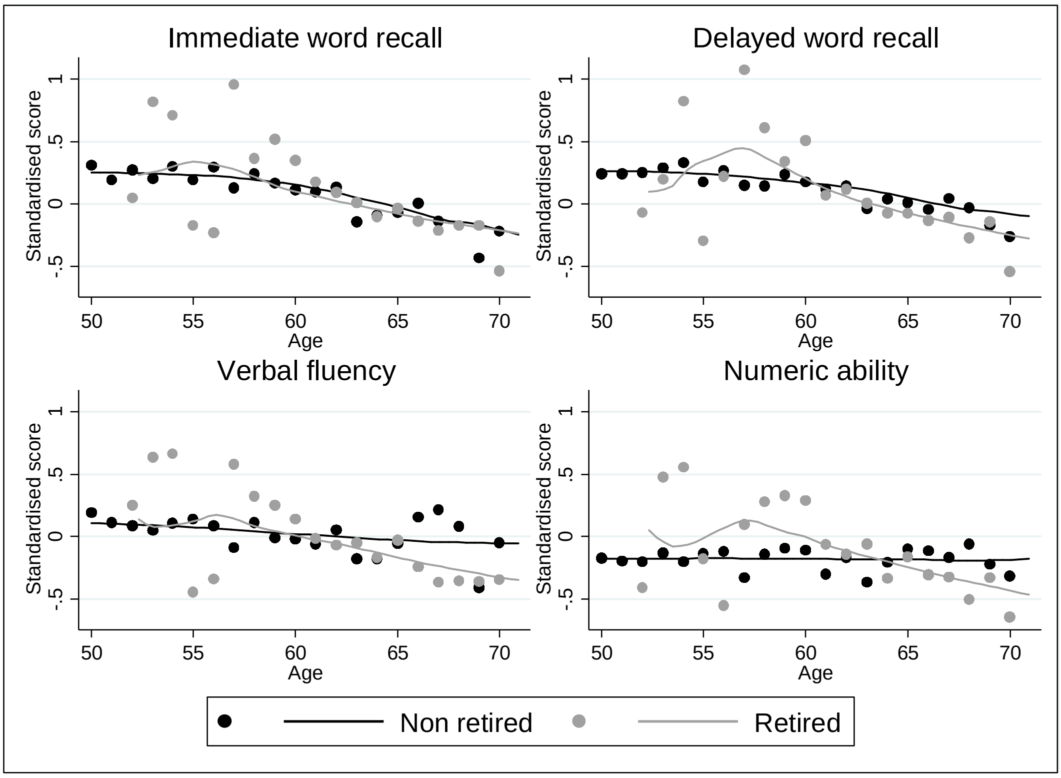
Note: the scatterplot identifies the averages by years in retirement computed by pooling observations in 1 year bands. The line is a local polynomial smoothed line fitted on actual observations.

Figure 3.4: Cognitive measures by age and retirement status, males



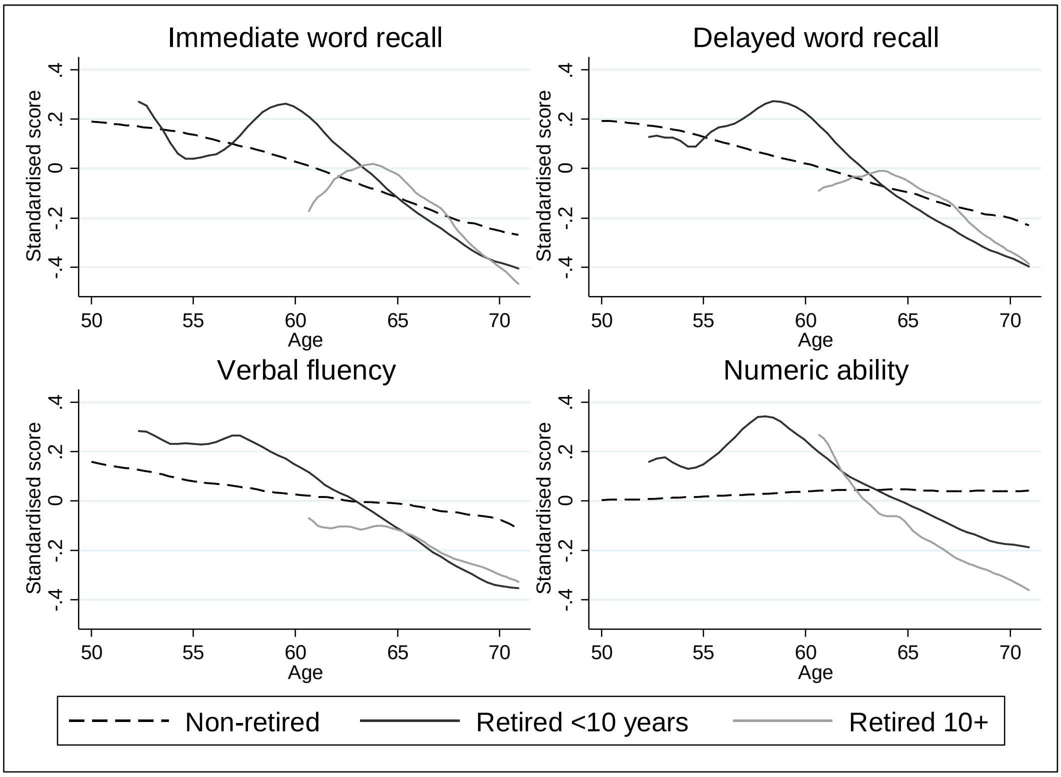
Note: the scatterplot identifies the age-specific averages computed by pooling observations in 1 year bands. The line is a local polynomial smoothed line fitted on actual observations.

Figure 3.5: Cognitive measures by age and retirement status, females



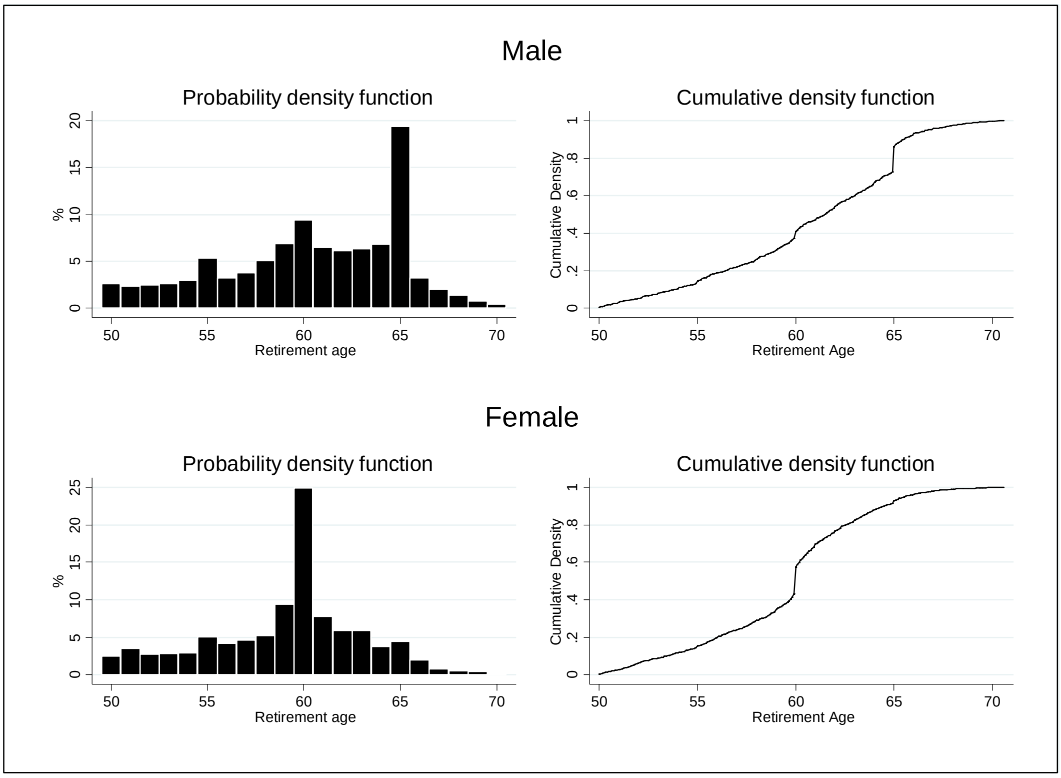
Note: the scatterplot identifies the age specific averages computed by pooling observations in 1 year bands. The line is a local polynomial smoothed line fitted on actual observations.

Figure 3.6: Cognitive measures by age and years since retirement



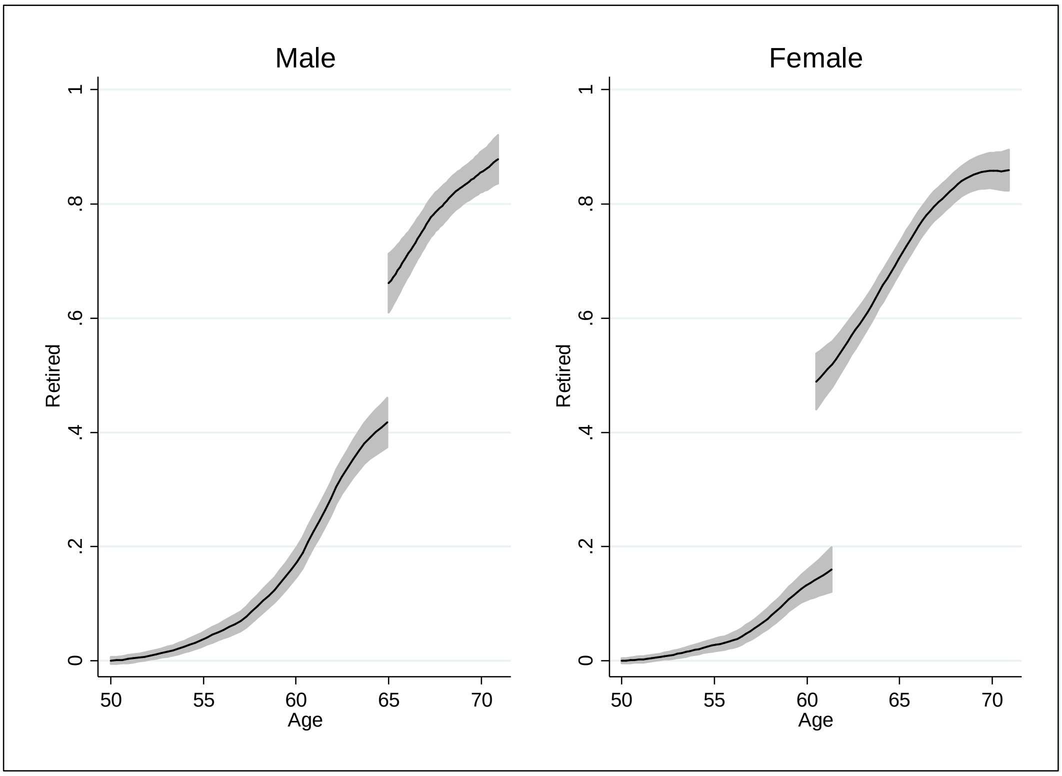
Note: local polynomial smoothed line fitted on actual observations.

Figure 3.7: Retirement age distribution



Note: Retirement age is only observed for retired respondents.

Figure 3.8: Retirement probability by age



Note: local polynomial smoothed line fitted on actual observations.

Table 3.1: Summary Statistics

	All (N=7936)		Male (N=3746)		Female (N=4190)		Retired (N=2553)		Non-retired (N=5383)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PANEL A										
Age	59.85	6.03	60.03	6.08	59.69	5.99	65.71	3.48	57.07	4.89
Male	0.47	0.50	1.00	0.00	0.00	0.00	0.45	0.50	0.48	0.50
Retired	0.32	0.47	0.30	0.46	0.34	0.47	1.00	0.00	0.00	0.00
Years since retirement	1.81	3.60	1.57	3.31	2.03	3.84	5.63	4.34	0.00	0.00
Years since state pension age	1.63	2.76	0.74	1.53	2.43	3.32	4.01	3.19	0.50	1.58
Low qualification	0.27	0.45	0.26	0.44	0.28	0.45	0.36	0.48	0.23	0.42
Routine job	0.11	0.32	0.14	0.35	0.09	0.28	0.12	0.33	0.11	0.31
Lives with partner	0.75	0.43	0.81	0.39	0.71	0.46	0.74	0.44	0.76	0.43
Good general health	0.81	0.39	0.80	0.40	0.82	0.38	0.77	0.42	0.83	0.37
England	0.83	0.38	0.83	0.38	0.83	0.38	0.83	0.38	0.83	0.38
Wales	0.05	0.22	0.05	0.22	0.05	0.22	0.05	0.22	0.05	0.22
Scotland	0.08	0.28	0.09	0.28	0.08	0.28	0.09	0.29	0.08	0.27
Northern Ireland	0.04	0.19	0.04	0.19	0.04	0.19	0.03	0.17	0.04	0.19
PANEL B										
Immediate word recall										
Raw	6.26	1.52	6.10	1.54	6.40	1.50	6.03	1.58	6.37	1.48
Standardised	-0.00	1.00	-0.10	1.01	0.09	0.98	-0.15	1.04	0.07	0.97
Delayed word recall										
Raw	5.13	1.88	4.90	1.85	5.32	1.89	4.84	1.90	5.26	1.86
Standardised	-0.00	1.00	-0.12	0.98	0.11	1.00	-0.15	1.01	0.07	0.99
Numeric ability										
Raw	3.75	1.04	3.99	1.01	3.54	1.03	3.70	1.07	3.78	1.03
Standardised	-0.00	1.00	0.23	0.97	-0.20	0.99	-0.05	1.02	0.02	0.99
Verbal fluency										
Raw	22.33	6.55	22.50	6.63	22.18	6.47	21.40	6.37	22.77	6.58
Standardised	-0.00	1.00	0.03	1.01	-0.02	0.99	-0.14	0.97	0.07	1.01

Table 3.2: Descriptive statistics by gender, retirement status and whether the respondent is above or below State Pension Age (SPA)

	Male				Female			
	Below SPA		Above SPA		Below SPA		Above SPA	
	Non-retired (N=2390)	Retired (N=375)	Non-retired (N=215)	Retired (N=766)	Non-retired (N=2249)	Retired (N=107)	Non-retired (N=529)	Retired (N=1305)
Immediate word recall	-0.01	0.07	-0.34	-0.40	0.22	0.39	-0.02	-0.12
Delayed word recall	-0.04	-0.01	-0.31	-0.37	0.23	0.46	0.05	-0.12
Numeric ability	0.24	0.47	0.23	0.08	-0.17	0.20	-0.20	-0.29
Verbal fluency	0.10	0.19	-0.08	-0.24	0.08	0.22	-0.04	-0.21
Age	56.55	61.76	67.21	68.02	54.95	58.33	64.32	66.10
Low qualification	0.24	0.15	0.33	0.38	0.20	0.07	0.31	0.44
Routine job	0.14	0.07	0.15	0.17	0.08	0.00	0.08	0.11
Lives with partner	0.80	0.81	0.84	0.81	0.71	0.74	0.71	0.69
Good general health	0.82	0.79	0.83	0.75	0.84	0.88	0.87	0.77
England	0.83	0.86	0.83	0.81	0.83	0.80	0.84	0.83
Wales	0.05	0.04	0.06	0.05	0.05	0.07	0.05	0.05
Scotland	0.08	0.09	0.08	0.09	0.08	0.10	0.07	0.09
Northern Ireland	0.04	0.02	0.04	0.04	0.04	0.02	0.03	0.03

Note: Standardised cognitive measures.

Table 3.3: OLS results

	MALES				FEMALES			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.022***	-0.022***	0.003	-0.018***	-0.018***	-0.017***	0.006*	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Years since retirement	-0.003	0.000	-0.005	-0.003	-0.000	-0.004	-0.005	-0.004
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Low qualification	-0.470***	-0.377***	-0.628***	-0.292***	-0.464***	-0.404***	-0.569***	-0.413***
	(0.038)	(0.037)	(0.037)	(0.039)	(0.034)	(0.034)	(0.032)	(0.034)
Routine job	-0.214***	-0.179***	-0.374***	-0.234***	-0.358***	-0.287***	-0.527***	-0.310***
	(0.046)	(0.044)	(0.047)	(0.046)	(0.058)	(0.057)	(0.054)	(0.050)
Lives with partner	0.077*	0.039	0.193***	0.166***	0.032	0.050	0.101***	0.087***
	(0.041)	(0.039)	(0.039)	(0.041)	(0.032)	(0.033)	(0.032)	(0.033)
Good health	0.261***	0.210***	0.243***	0.214***	0.222***	0.239***	0.220***	0.163***
	(0.041)	(0.039)	(0.041)	(0.041)	(0.040)	(0.040)	(0.040)	(0.037)
Northern Ireland	-0.134	0.046	0.180**	-0.289***	-0.037	0.060	0.163**	-0.370***
	(0.087)	(0.080)	(0.076)	(0.092)	(0.080)	(0.083)	(0.074)	(0.084)
Wales	0.021	-0.124*	-0.078	-0.248***	-0.184***	-0.242***	-0.146**	-0.290***
	(0.062)	(0.070)	(0.070)	(0.063)	(0.066)	(0.064)	(0.068)	(0.056)
Scotland	-0.031	0.010	0.007	-0.004	-0.058	-0.002	0.121**	-0.202***
	(0.054)	(0.052)	(0.052)	(0.059)	(0.054)	(0.054)	(0.053)	(0.052)
_cons	0.012	0.030	0.068	0.035	0.243***	0.196***	-0.300***	0.096**
	(0.057)	(0.054)	(0.056)	(0.056)	(0.049)	(0.050)	(0.050)	(0.049)
N	3746	3746	3746	3746	4190	4190	4190	4190

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: IV First stage

	MALES (1) Years since retirement	FEMALES (2) Years since retirement
Age	0.155***	0.021**
	(0.009)	(0.010)
Years since SPA	0.768***	0.752***
	(0.058)	(0.030)
Low qualification	-0.255**	0.342***
	(0.105)	(0.116)
Routine job	-0.343***	-0.323*
	(0.124)	(0.167)
Lives with partner	0.043	0.040
	(0.110)	(0.096)
Good health	-0.311***	-0.539***
	(0.119)	(0.121)
Northern Ireland	0.215	0.001
	(0.237)	(0.193)
Wales	-0.276*	0.231
	(0.163)	(0.220)
Scotland	0.109	0.254
	(0.161)	(0.165)
_cons	-0.231	0.309**
	(0.144)	(0.123)
N	3746	4190
Fstat	173.959	641.567

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: IV-Second stage

	MALES				FEMALES			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.003	-0.012*	0.028***	0.004	-0.003	0.000	0.019***	-0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Years since retirement	-0.070***	-0.035*	-0.089***	-0.078***	-0.041***	-0.048***	-0.040***	-0.015
	(0.020)	(0.019)	(0.019)	(0.019)	(0.013)	(0.013)	(0.013)	(0.013)
Low qualification	-0.485***	-0.385***	-0.647***	-0.309***	-0.444***	-0.383***	-0.552***	-0.408***
	(0.039)	(0.037)	(0.038)	(0.040)	(0.035)	(0.035)	(0.033)	(0.034)
Routine job	-0.233***	-0.189***	-0.398***	-0.255***	-0.367***	-0.296***	-0.535***	-0.313***
	(0.047)	(0.045)	(0.048)	(0.047)	(0.058)	(0.058)	(0.054)	(0.050)
Lives with partner	0.080*	0.040	0.196***	0.169***	0.031	0.050	0.100***	0.087***
	(0.042)	(0.039)	(0.040)	(0.041)	(0.032)	(0.033)	(0.032)	(0.033)
Good health	0.240***	0.198***	0.216***	0.190***	0.199***	0.214***	0.200***	0.157***
	(0.043)	(0.040)	(0.043)	(0.042)	(0.040)	(0.040)	(0.040)	(0.037)
Northern Ireland	-0.114	0.057	0.205***	-0.267***	-0.034	0.063	0.166**	-0.369***
	(0.089)	(0.080)	(0.073)	(0.091)	(0.081)	(0.084)	(0.074)	(0.085)
Wales	0.004	-0.133*	-0.099	-0.267***	-0.177***	-0.234***	-0.139**	-0.288***
	(0.062)	(0.070)	(0.070)	(0.063)	(0.067)	(0.065)	(0.069)	(0.056)
Scotland	-0.024	0.014	0.015	0.004	-0.048	0.009	0.129**	-0.199***
	(0.054)	(0.053)	(0.053)	(0.061)	(0.054)	(0.054)	(0.053)	(0.052)
_cons	-0.056	-0.006	-0.019	-0.043	0.186***	0.134**	-0.349***	0.080
	(0.061)	(0.057)	(0.059)	(0.061)	(0.052)	(0.053)	(0.053)	(0.052)
N	3746	3746	3746	3746	4190	4190	4190	4190

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Reduced form estimates

	MALES				FEMALES			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.014***	-0.017***	0.014***	-0.008**	-0.004	-0.001	0.018***	-0.008
	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Years since SPA	-0.053***	-0.027*	-0.068***	-0.060***	-0.031***	-0.036***	-0.030***	-0.012
	(0.015)	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.010)	(0.010)
Low qualification	-0.467***	-0.376***	-0.625***	-0.289***	-0.458***	-0.399***	-0.566***	-0.413***
	(0.038)	(0.037)	(0.037)	(0.039)	(0.034)	(0.034)	(0.032)	(0.034)
Routine job	-0.209***	-0.177***	-0.368***	-0.229***	-0.354***	-0.281***	-0.522***	-0.308***
	(0.046)	(0.044)	(0.047)	(0.046)	(0.058)	(0.057)	(0.054)	(0.050)
Lives with partner	0.077*	0.039	0.192***	0.166***	0.030	0.048	0.098***	0.087***
	(0.041)	(0.039)	(0.039)	(0.041)	(0.032)	(0.033)	(0.032)	(0.033)
Good health	0.262***	0.209***	0.244***	0.214***	0.221***	0.240***	0.221***	0.165***
	(0.041)	(0.039)	(0.041)	(0.041)	(0.040)	(0.040)	(0.040)	(0.037)
Northern Ireland	-0.129	0.049	0.186**	-0.283***	-0.034	0.063	0.166**	-0.369***
	(0.087)	(0.080)	(0.075)	(0.091)	(0.080)	(0.083)	(0.074)	(0.085)
Wales	0.024	-0.123*	-0.074	-0.246***	-0.186***	-0.245***	-0.148**	-0.292***
	(0.062)	(0.070)	(0.069)	(0.062)	(0.066)	(0.065)	(0.068)	(0.056)
Scotland	-0.031	0.010	0.006	-0.005	-0.059	-0.004	0.119**	-0.203***
	(0.053)	(0.053)	(0.052)	(0.060)	(0.054)	(0.054)	(0.052)	(0.052)
_cons	-0.040	0.002	0.002	-0.024	0.174***	0.119**	-0.361***	0.076
	(0.058)	(0.056)	(0.056)	(0.058)	(0.053)	(0.054)	(0.055)	(0.054)
N	3746	3746	3746	3746	4190	4190	4190	4190

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Interaction with low level of qualifications, 1st Stage

	MALES		FEMALES	
	(1)	(2)	(3)	(4)
	Years since retirement	Low qualification * Years since retirement	Years since retirement	Low qualification * Years since retirement
Age	0.164***	-0.000	0.029***	-0.000
	(0.011)	(0.000)	(0.011)	(0.001)
Years since SPA	0.731***	0.001	0.697***	0.000
	(0.071)	(0.002)	(0.037)	(0.002)
Low qualification	0.033	-0.587***	-0.002	-0.075
	(0.116)	(0.103)	(0.085)	(0.074)
Low qualification *				
Age	-0.037*	0.129***	-0.004	0.026
	(0.022)	(0.019)	(0.023)	(0.020)
Years since SPA	0.132	0.860***	0.126*	0.823***
	(0.127)	(0.105)	(0.065)	(0.054)
Routine job	-0.344***	-0.027	-0.320*	-0.181
	(0.124)	(0.096)	(0.167)	(0.153)
Lives with partner	0.046	-0.020	0.041	-0.049
	(0.110)	(0.064)	(0.096)	(0.062)
Good health	-0.316***	-0.227***	-0.535***	-0.260***
	(0.119)	(0.075)	(0.121)	(0.086)
Northern Ireland	0.198	0.205	-0.013	0.209*
	(0.236)	(0.165)	(0.191)	(0.127)
Wales	-0.273*	-0.060	0.214	0.120
	(0.163)	(0.101)	(0.220)	(0.155)
Scotland	0.103	0.070	0.253	0.289***
	(0.162)	(0.085)	(0.163)	(0.106)
_cons	-0.290**	0.199**	0.346***	0.229***
	(0.144)	(0.084)	(0.121)	(0.081)
N	3746	3746	4190	4190
Fstat	87.046	33.437	295.966	117.533

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Interaction with low level of qualifications, 2nd stage

	MALES				FEMALES			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.000	-0.014**	0.028***	0.004	-0.001	0.002	0.019***	-0.004
	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
Years since retirement	-0.079***	-0.031	-0.092***	-0.094***	-0.043***	-0.053***	-0.041**	-0.021
	(0.025)	(0.023)	(0.023)	(0.024)	(0.016)	(0.017)	(0.016)	(0.017)
Low qualification	-0.457***	-0.477***	-0.678***	-0.449***	-0.406***	-0.343***	-0.560***	-0.295***
	(0.100)	(0.101)	(0.104)	(0.105)	(0.087)	(0.093)	(0.088)	(0.095)
Low qualification *								
Age	-0.007	0.011	0.002	0.009	-0.006	-0.008	0.000	-0.017
	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
Years since retirement	0.027	-0.018	0.004	0.026	0.011	0.018	0.003	0.027
	(0.042)	(0.039)	(0.042)	(0.040)	(0.028)	(0.028)	(0.028)	(0.027)
Routine job	-0.236***	-0.187***	-0.399***	-0.258***	-0.366***	-0.295***	-0.535***	-0.310***
	(0.047)	(0.045)	(0.049)	(0.048)	(0.058)	(0.058)	(0.054)	(0.050)
Lives with partner	0.081*	0.039	0.196***	0.169***	0.032	0.051	0.100***	0.090***
	(0.042)	(0.039)	(0.040)	(0.042)	(0.032)	(0.033)	(0.032)	(0.033)
Good health	0.243***	0.197***	0.217***	0.195***	0.200***	0.216***	0.200***	0.160***
	(0.043)	(0.040)	(0.043)	(0.043)	(0.040)	(0.040)	(0.040)	(0.038)
Northern Ireland	-0.120	0.061	0.204***	-0.272***	-0.036	0.059	0.165**	-0.375***
	(0.089)	(0.081)	(0.073)	(0.092)	(0.081)	(0.084)	(0.075)	(0.085)
Wales	0.004	-0.134*	-0.100	-0.270***	-0.178***	-0.236***	-0.139**	-0.292***
	(0.062)	(0.070)	(0.070)	(0.063)	(0.067)	(0.065)	(0.069)	(0.056)
Scotland	-0.026	0.015	0.015	0.001	-0.051	0.005	0.129**	-0.205***
	(0.055)	(0.053)	(0.053)	(0.061)	(0.055)	(0.054)	(0.053)	(0.052)
_cons	-0.068	0.014	-0.015	-0.025	0.178***	0.124**	-0.348***	0.056
	(0.065)	(0.063)	(0.063)	(0.066)	(0.055)	(0.057)	(0.057)	(0.056)
N	3746	3746	3746	3746	4190	4190	4190	4190

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Interaction with routine job, 1st Stage

	MALES		FEMALES	
	(1)	(2)	(3)	(4)
	Years since retirement	Routine x Years since retirement	Years since retirement	Routine x Years since retirement
Age	0.157***	-0.001	0.023**	-0.000
	(0.010)	(0.000)	(0.010)	(0.000)
Years since SPA	0.813***	-0.001	0.750***	-0.001
	(0.064)	(0.001)	(0.032)	(0.001)
Low qualification	-0.254**	0.061	0.344***	0.039
	(0.105)	(0.041)	(0.116)	(0.027)
Routine job	0.010	-0.600***	-0.178*	-0.056
	(0.145)	(0.131)	(0.107)	(0.084)
Routine job *				
Age	-0.012	0.141***	-0.023	0.005
	(0.029)	(0.027)	(0.030)	(0.028)
Years since SPA	-0.257*	0.561***	0.034	0.788***
	(0.154)	(0.140)	(0.087)	(0.081)
Lives with partner	0.047	-0.101**	0.039	-0.010
	(0.110)	(0.049)	(0.096)	(0.030)
Good health	-0.307**	-0.054	-0.537***	-0.146***
	(0.119)	(0.048)	(0.121)	(0.046)
Northern Ireland	0.187	-0.009	0.001	0.144*
	(0.236)	(0.014)	(0.193)	(0.082)
Wales	-0.285*	-0.090*	0.231	-0.064
	(0.160)	(0.050)	(0.220)	(0.071)
Scotland	0.090	0.080	0.254	0.048
	(0.161)	(0.067)	(0.165)	(0.059)
_cons	-0.282*	0.119**	0.297**	0.119***
	(0.146)	(0.054)	(0.124)	(0.043)
N	3746	3746	4190	4190
Fstat	88.101	8.146	324.505	47.137

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: Interaction with routine job, 2nd Stage

	MALES				FEMALES			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.005	-0.015**	0.025***	0.006	-0.000	0.003	0.022***	-0.007
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Years since retirement	-0.069***	-0.031*	-0.081***	-0.089***	-0.048***	-0.056***	-0.048***	-0.022*
	(0.020)	(0.019)	(0.019)	(0.020)	(0.013)	(0.014)	(0.013)	(0.013)
Low qualification	-0.485***	-0.383***	-0.641***	-0.317***	-0.443***	-0.381***	-0.551***	-0.406***
	(0.039)	(0.038)	(0.039)	(0.041)	(0.035)	(0.035)	(0.033)	(0.034)
Routine job	-0.378***	-0.387***	-0.488***	-0.266**	-0.269**	-0.198	-0.437***	-0.375***
	(0.121)	(0.121)	(0.134)	(0.126)	(0.134)	(0.147)	(0.136)	(0.135)
Routine job *								
Age	0.017	0.025	0.019	-0.010	-0.028	-0.029	-0.029	-0.009
	(0.020)	(0.019)	(0.022)	(0.019)	(0.021)	(0.021)	(0.022)	(0.020)
Years since retirement	-0.020	-0.046	-0.076	0.084	0.082*	0.085*	0.084*	0.062
	(0.072)	(0.070)	(0.083)	(0.068)	(0.048)	(0.046)	(0.048)	(0.042)
Lives with partner	0.077*	0.034	0.188***	0.177***	0.032	0.051	0.101***	0.089***
	(0.043)	(0.041)	(0.042)	(0.042)	(0.032)	(0.033)	(0.032)	(0.033)
Good health	0.238***	0.195***	0.214***	0.190***	0.209***	0.224***	0.210***	0.163***
	(0.043)	(0.040)	(0.043)	(0.043)	(0.041)	(0.041)	(0.040)	(0.038)
Northern Ireland	-0.108	0.063	0.203***	-0.259***	-0.048	0.048	0.151**	-0.382***
	(0.089)	(0.080)	(0.073)	(0.091)	(0.082)	(0.085)	(0.076)	(0.085)
Wales	0.006	-0.133*	-0.103	-0.261***	-0.170**	-0.227***	-0.132*	-0.283***
	(0.062)	(0.070)	(0.070)	(0.063)	(0.067)	(0.066)	(0.070)	(0.056)
Scotland	-0.019	0.021	0.020	0.001	-0.050	0.007	0.127**	-0.199***
	(0.054)	(0.054)	(0.054)	(0.061)	(0.054)	(0.054)	(0.053)	(0.052)
_cons	-0.035	0.024	-0.001	-0.047	0.169***	0.117**	-0.366***	0.077
	(0.064)	(0.061)	(0.062)	(0.065)	(0.053)	(0.054)	(0.055)	(0.054)
N	3746	3746	3746	3746	4190	4190	4190	4190

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.8 Appendix: Complementary Tables

Table 3.A1: Akaike's information criterion after reduced form, anticipation of SPA, placebo

	MALES				FEMALES			
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Years since SPA	10285.084	10201.892	9768.525	10462.664	11262.491	11531.770	11176.614	11398.528
Years since SPA-2	10286.599	10202.684	9769.247	10463.321	11263.305	11533.202	11179.668	11398.850
Years since SPA-4	10290.163	10204.053	9770.209	10467.633	11265.363	11535.901	11183.302	11399.202
Years since SPA-6	10294.292	10205.094	9771.049	10471.927	11267.581	11537.914	11186.161	11399.761
Years since SPA-8	10296.845	10205.420	9777.469	10476.310	11270.040	11540.714	11187.025	11399.970
Years since SPA-10	10298.541	10205.015	9783.792	10478.965	11272.020	11543.251	11186.639	11399.952

Table 3.A2: Akaike's information criterion after reduced form, posticipation of SPA, placebo

	MALES				FEMALES			
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Years since SPA	10285.084	10201.892	9768.525	10462.664	11262.491	11531.770	11176.614	11398.528
Years since SPA+1	10285.434	10202.033	9768.041	10462.459	11262.837	11532.272	11177.998	11398.689
Years since SPA+2	10286.599	10202.684	9769.247	10463.321	11263.305	11533.202	11179.668	11398.850
Years since SPA+3	10287.956	10203.076	9769.887	10465.479	11264.180	11534.439	11181.483	11398.997
Years since SPA+4	10290.163	10204.053	9770.209	10467.633	11265.363	11535.901	11183.302	11399.202
Years since SPA+5	10292.296	10204.624	9769.525	10469.771	11266.624	11537.100	11185.054	11399.525

Table 3.A3: IV estimates excluding people who retired before reaching state pension age

	MALE				FEMALE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.019***	-0.022***	0.010**	-0.010**	-0.011**	-0.008	0.011**	-0.011**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Years since retirement	-0.030	0.006	-0.088***	-0.070**	-0.039**	-0.053***	-0.034*	-0.011
	(0.035)	(0.033)	(0.033)	(0.033)	(0.020)	(0.020)	(0.019)	(0.019)
Low qualification	-0.485***	-0.387***	-0.624***	-0.298***	-0.461***	-0.389***	-0.530***	-0.401***
	(0.042)	(0.042)	(0.041)	(0.044)	(0.038)	(0.038)	(0.036)	(0.037)
Routine job	-0.223***	-0.183***	-0.378***	-0.228***	-0.366***	-0.285***	-0.531***	-0.319***
	(0.049)	(0.048)	(0.051)	(0.051)	(0.063)	(0.062)	(0.059)	(0.055)
Lives with partner	0.083*	0.020	0.168***	0.186***	0.017	0.032	0.096***	0.110***
	(0.046)	(0.044)	(0.043)	(0.045)	(0.035)	(0.036)	(0.035)	(0.036)
Good health	0.202***	0.182***	0.193***	0.206***	0.209***	0.222***	0.224***	0.155***
	(0.048)	(0.045)	(0.047)	(0.046)	(0.044)	(0.043)	(0.045)	(0.041)
Northern Ireland	-0.136	0.077	0.304***	-0.232**	-0.063	0.041	0.151*	-0.390***
	(0.098)	(0.092)	(0.074)	(0.103)	(0.084)	(0.086)	(0.077)	(0.088)
Wales	0.014	-0.141*	-0.037	-0.261***	-0.184**	-0.231***	-0.165**	-0.309***
	(0.069)	(0.080)	(0.075)	(0.069)	(0.076)	(0.072)	(0.079)	(0.063)
Scotland	-0.028	-0.018	0.044	0.005	-0.039	0.014	0.108*	-0.219***
	(0.061)	(0.060)	(0.060)	(0.067)	(0.061)	(0.059)	(0.060)	(0.058)
_cons	0.012	0.040	0.087	-0.048	0.200***	0.148***	-0.327***	0.064
	(0.065)	(0.062)	(0.062)	(0.063)	(0.054)	(0.055)	(0.056)	(0.054)
N	2916	2916	2916	2916	3554	3554	3554	3554

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A4: IV estimates including intercept and slope effect of retirement on cognitive abilities

	MALES				FEMALES			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.006	-0.017*	0.022**	-0.002	-0.004	-0.000	0.014*	-0.011
	(0.010)	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)
Retired	0.117	0.183	0.211	0.226	0.045	0.017	0.160	0.118
	(0.349)	(0.326)	(0.325)	(0.321)	(0.175)	(0.181)	(0.175)	(0.170)
Years since retirement	-0.079**	-0.049	-0.105***	-0.095***	-0.043***	-0.049***	-0.050***	-0.022
	(0.037)	(0.034)	(0.035)	(0.034)	(0.016)	(0.016)	(0.016)	(0.015)
Low qualification	-0.483***	-0.382***	-0.644***	-0.305***	-0.445***	-0.383***	-0.553***	-0.408***
	(0.039)	(0.037)	(0.039)	(0.040)	(0.035)	(0.035)	(0.033)	(0.034)
Routine job	-0.233***	-0.188***	-0.398***	-0.255***	-0.366***	-0.296***	-0.533***	-0.312***
	(0.047)	(0.045)	(0.048)	(0.047)	(0.058)	(0.058)	(0.054)	(0.050)
Lives with partner	0.081*	0.042	0.198***	0.171***	0.031	0.049	0.100***	0.087***
	(0.042)	(0.039)	(0.040)	(0.042)	(0.032)	(0.033)	(0.032)	(0.033)
Good health	0.240***	0.199***	0.217***	0.190***	0.200***	0.214***	0.203***	0.159***
	(0.043)	(0.040)	(0.043)	(0.042)	(0.040)	(0.040)	(0.041)	(0.038)
Northern Ireland	-0.111	0.061	0.210***	-0.261***	-0.033	0.063	0.171**	-0.366***
	(0.089)	(0.081)	(0.074)	(0.092)	(0.081)	(0.084)	(0.074)	(0.084)
Wales	0.005	-0.133*	-0.098	-0.267***	-0.175***	-0.233***	-0.135*	-0.285***
	(0.062)	(0.070)	(0.070)	(0.063)	(0.067)	(0.066)	(0.069)	(0.056)
Scotland	-0.025	0.013	0.014	0.002	-0.048	0.009	0.129**	-0.199***
	(0.054)	(0.053)	(0.054)	(0.061)	(0.054)	(0.054)	(0.053)	(0.052)
_cons	-0.048	0.007	-0.004	-0.027	0.189***	0.135**	-0.339***	0.088
	(0.063)	(0.061)	(0.062)	(0.063)	(0.053)	(0.054)	(0.055)	(0.054)
N	3746	3746	3746	3746	4190	4190	4190	4190

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A5: IV estimates including intercept and slope effect of retirement on cognitive abilities, routine versus non routine occupations

	NON ROUTINE OCCUPATIONS				ROUTINE OCCUPATIONS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.006	-0.011	0.017***	-0.006	-0.015	-0.016	0.014	-0.010
	(0.007)	(0.007)	(0.006)	(0.007)	(0.013)	(0.013)	(0.014)	(0.014)
Retired	-0.121	0.014	0.012	-0.054	0.219	0.379	-0.140	-0.060
	(0.184)	(0.183)	(0.171)	(0.177)	(0.307)	(0.278)	(0.327)	(0.253)
Years since retirement	-0.027	-0.033**	-0.044***	-0.026	-0.031	-0.046	-0.004	0.031
	(0.017)	(0.017)	(0.015)	(0.016)	(0.043)	(0.040)	(0.045)	(0.034)
Male	-0.216***	-0.245***	0.399***	0.024	-0.044	-0.108	0.547***	0.196***
	(0.023)	(0.024)	(0.023)	(0.025)	(0.077)	(0.074)	(0.074)	(0.069)
Low qualification	-0.473***	-0.381***	-0.597***	-0.353***	-0.388***	-0.416***	-0.540***	-0.347***
	(0.028)	(0.027)	(0.026)	(0.028)	(0.070)	(0.069)	(0.070)	(0.067)
Lives with partner	0.057**	0.058**	0.127***	0.129***	-0.002	-0.039	0.207***	0.053
	(0.027)	(0.027)	(0.026)	(0.028)	(0.076)	(0.075)	(0.080)	(0.073)
Good health	0.229***	0.219***	0.237***	0.204***	0.197**	0.164**	0.125	0.047
	(0.031)	(0.031)	(0.032)	(0.031)	(0.080)	(0.076)	(0.079)	(0.070)
Northern Ireland	-0.105*	0.039	0.155***	-0.318***	0.114	0.245	0.320	-0.467**
	(0.062)	(0.062)	(0.055)	(0.066)	(0.211)	(0.156)	(0.199)	(0.197)
Wales	-0.069	-0.153***	-0.094*	-0.268***	-0.215*	-0.387***	-0.217	-0.241**
	(0.049)	(0.051)	(0.052)	(0.046)	(0.128)	(0.137)	(0.152)	(0.109)
Scotland	-0.031	0.015	0.075*	-0.093**	-0.079	-0.013	0.039	-0.185**
	(0.041)	(0.041)	(0.040)	(0.044)	(0.103)	(0.097)	(0.106)	(0.085)
_cons	0.192***	0.190***	-0.362***	0.011	-0.179	-0.020	-0.896***	-0.240**
	(0.043)	(0.042)	(0.042)	(0.043)	(0.116)	(0.120)	(0.118)	(0.112)
N	7034	7034	7034	7034	902	902	902	902

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A6: IV estimates with people aged 50 to 80

	MALE				FEMALE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.008**	-0.010**	0.016***	-0.006	-0.003	-0.002	0.016***	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Years since retirement	-0.047***	-0.043***	-0.048***	-0.038***	-0.037***	-0.041***	-0.033***	-0.021***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Low qualification	-0.414***	-0.339***	-0.595***	-0.277***	-0.402***	-0.344***	-0.523***	-0.403***
	(0.032)	(0.030)	(0.032)	(0.033)	(0.030)	(0.031)	(0.029)	(0.029)
Routine job	-0.226***	-0.189***	-0.399***	-0.240***	-0.298***	-0.247***	-0.489***	-0.244***
	(0.039)	(0.038)	(0.042)	(0.039)	(0.049)	(0.048)	(0.045)	(0.041)
Lives with partner	0.068*	0.025	0.206***	0.157***	0.027	0.022	0.084***	0.087***
	(0.035)	(0.033)	(0.035)	(0.035)	(0.028)	(0.029)	(0.028)	(0.028)
Good health	0.252***	0.184***	0.233***	0.216***	0.211***	0.208***	0.189***	0.154***
	(0.034)	(0.033)	(0.036)	(0.034)	(0.034)	(0.034)	(0.034)	(0.032)
Northern Ireland	-0.052	0.102	0.185***	-0.289***	-0.077	0.012	0.102	-0.336***
	(0.070)	(0.067)	(0.067)	(0.075)	(0.070)	(0.073)	(0.069)	(0.073)
Wales	-0.026	-0.110*	-0.064	-0.249***	-0.127**	-0.209***	-0.148**	-0.261***
	(0.054)	(0.060)	(0.059)	(0.054)	(0.057)	(0.055)	(0.059)	(0.049)
Scotland	-0.027	0.017	0.058	-0.017	-0.064	0.004	0.103**	-0.185***
	(0.047)	(0.047)	(0.049)	(0.053)	(0.049)	(0.048)	(0.046)	(0.045)
_cons	0.093*	0.139***	0.063	0.092*	0.301***	0.287***	-0.244***	0.182***
	(0.052)	(0.049)	(0.052)	(0.053)	(0.045)	(0.046)	(0.047)	(0.046)
N	4798	4798	4798	4798	5169	5169	5169	5169

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A7: IV estimates excluding general health from the regressors

	MALES				FEMALES			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Immediate recall	Delayed recall	Numeric ability	Fluency	Immediate recall	Delayed recall	Numeric ability	Fluency
Age	-0.003	-0.012**	0.027***	0.004	-0.003	0.000	0.019***	-0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Years since retirement	-0.070***	-0.036*	-0.090***	-0.079***	-0.041***	-0.049***	-0.041***	-0.016
	(0.020)	(0.019)	(0.019)	(0.019)	(0.013)	(0.013)	(0.013)	(0.013)
Low qualification	-0.507***	-0.403***	-0.667***	-0.326***	-0.461***	-0.400***	-0.569***	-0.420***
	(0.039)	(0.037)	(0.038)	(0.040)	(0.035)	(0.036)	(0.033)	(0.034)
Routine job	-0.243***	-0.197***	-0.407***	-0.263***	-0.388***	-0.319***	-0.555***	-0.329***
	(0.047)	(0.045)	(0.048)	(0.047)	(0.058)	(0.058)	(0.054)	(0.050)
Lives with partner	0.092**	0.050	0.207***	0.178***	0.047	0.066**	0.116***	0.100***
	(0.042)	(0.040)	(0.040)	(0.042)	(0.032)	(0.033)	(0.032)	(0.033)
Northern Ireland	-0.107	0.063	0.212***	-0.261***	-0.028	0.069	0.172**	-0.365***
	(0.089)	(0.080)	(0.072)	(0.092)	(0.080)	(0.083)	(0.075)	(0.084)
Wales	-0.008	-0.143**	-0.110	-0.277***	-0.182***	-0.240***	-0.145**	-0.293***
	(0.062)	(0.070)	(0.070)	(0.063)	(0.067)	(0.065)	(0.069)	(0.056)
Scotland	-0.025	0.013	0.015	0.003	-0.039	0.019	0.139***	-0.191***
	(0.054)	(0.054)	(0.053)	(0.061)	(0.055)	(0.054)	(0.053)	(0.052)
_cons	0.140***	0.156***	0.158***	0.113**	0.345***	0.305***	-0.189***	0.206***
	(0.052)	(0.050)	(0.050)	(0.053)	(0.043)	(0.045)	(0.045)	(0.047)
N	3746	3746	3746	3746	4190	4190	4190	4190

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A8: Different age specifications, IV-Estimates, male

	Immediate recall			Delayed recall			Numeric ability			Fluency		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age	-0.003	-0.056*		-0.012*	-0.057**		0.028***	0.013		0.004	-0.056*	
	(0.006)	(0.029)		(0.006)	(0.027)		(0.006)	(0.025)		(0.006)	(0.030)	
Years since ret.	-0.070***	-0.238**	-0.123**	-0.035*	-0.178*	-0.091*	-0.089***	-0.137	-0.044	-0.078***	-0.271**	-0.091*
	(0.020)	(0.118)	(0.055)	(0.019)	(0.105)	(0.049)	(0.019)	(0.096)	(0.044)	(0.019)	(0.121)	(0.049)
Age*Age/10		0.050*			0.042			0.014			0.057*	
		(0.030)			(0.028)			(0.025)			(0.031)	
53-55			-0.069			-0.130**			0.002			-0.088
			(0.053)			(0.056)			(0.053)			(0.059)
56-58			-0.106*			-0.161***			0.126**			-0.061
			(0.057)			(0.058)			(0.053)			(0.063)
59-61			-0.045			-0.140**			0.193***			-0.015
			(0.068)			(0.065)			(0.060)			(0.071)
62-64			0.046			-0.073			0.203**			0.049
			(0.112)			(0.103)			(0.092)			(0.104)
65-67			0.093			-0.033			0.257			0.076
			(0.195)			(0.179)			(0.159)			(0.173)
68-70			0.233			0.070			0.190			0.097
			(0.323)			(0.292)			(0.258)			(0.292)
low qualification	-0.485***	-0.529***	-0.500***	-0.385***	-0.422***	-0.400***	-0.647***	-0.660***	-0.636***	-0.309***	-0.359***	-0.313***
	(0.039)	(0.055)	(0.043)	(0.037)	(0.049)	(0.040)	(0.038)	(0.046)	(0.040)	(0.040)	(0.057)	(0.043)
routine job	-0.233***	-0.289***	-0.250***	-0.189***	-0.236***	-0.207***	-0.398***	-0.414***	-0.384***	-0.255***	-0.320***	-0.259***
	(0.047)	(0.065)	(0.051)	(0.045)	(0.060)	(0.048)	(0.048)	(0.057)	(0.049)	(0.047)	(0.067)	(0.050)
lives with partner	0.080*	0.089*	0.083*	0.040	0.048	0.044	0.196***	0.199***	0.195***	0.169***	0.179***	0.170***
	(0.042)	(0.048)	(0.043)	(0.039)	(0.044)	(0.041)	(0.040)	(0.041)	(0.039)	(0.041)	(0.050)	(0.042)
Good health	0.240***	0.184***	0.221***	0.198***	0.151***	0.178***	0.216***	0.200***	0.230***	0.190***	0.126**	0.184***
	(0.043)	(0.062)	(0.046)	(0.040)	(0.056)	(0.043)	(0.043)	(0.055)	(0.043)	(0.042)	(0.064)	(0.045)
Northern Ireland	-0.114	-0.070	-0.098	0.057	0.094	0.072	0.205***	0.218***	0.195***	-0.267***	-0.216**	-0.261***
	(0.089)	(0.107)	(0.092)	(0.080)	(0.093)	(0.083)	(0.073)	(0.078)	(0.074)	(0.091)	(0.110)	(0.093)
Wales	0.004	-0.046	-0.013	-0.133*	-0.176**	-0.153**	-0.099	-0.113	-0.090	-0.267***	-0.324***	-0.275***
	(0.062)	(0.078)	(0.065)	(0.070)	(0.081)	(0.072)	(0.070)	(0.077)	(0.070)	(0.063)	(0.083)	(0.064)
Scotland	-0.024	-0.008	-0.018	0.014	0.027	0.020	0.015	0.020	0.011	0.004	0.022	0.005
	(0.054)	(0.067)	(0.057)	(0.053)	(0.063)	(0.056)	(0.053)	(0.056)	(0.052)	(0.061)	(0.074)	(0.061)
_cons	-0.056	0.107	0.002	-0.006	0.132	0.053	-0.019	0.027	0.041	-0.043	0.144	0.020
	(0.061)	(0.109)	(0.066)	(0.057)	(0.100)	(0.063)	(0.059)	(0.097)	(0.062)	(0.061)	(0.113)	(0.065)
N	3746	3746	3746	3746	3746	3746	3746	3746	3746	3746	3746	3746
AIC	10285.084	10286.385	10292.769	10201.892	10202.514	10208.416	9768.525	9769.237	9775.878	10462.664	10463.746	10471.657
BIC	10347.368	10354.898	10386.196	10264.176	10271.027	10301.842	9830.810	9837.750	9869.305	10524.949	10532.258	10565.084

Robust standard errors in parentheses; AIC and BIC from reduced form estimates; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A9: Different age specifications, IV- Estimates, female

	Immediate recall			Delayed recall			Numeric ability			Fluency		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age	-0.003	0.003		0.000	0.005		0.019***	0.019		-0.008	-0.002	
	(0.006)	(0.023)		(0.006)	(0.024)		(0.006)	(0.023)		(0.006)	(0.024)	
Years since ret.	-0.041***	-0.026	-0.105***	-0.048***	-0.035	-0.087**	-0.040***	-0.040	-0.078**	-0.015	-0.001	-0.056
	(0.013)	(0.066)	(0.038)	(0.013)	(0.068)	(0.037)	(0.013)	(0.067)	(0.035)	(0.013)	(0.067)	(0.035)
Age*Age/10		-0.006			-0.005			-0.000			-0.006	
		(0.024)			(0.025)			(0.024)			(0.025)	
53-55			-0.017			0.028			0.041			-0.024
			(0.048)			(0.051)			(0.050)			(0.053)
56-58			0.010			0.007			0.049			-0.052
			(0.052)			(0.055)			(0.051)			(0.053)
59-61			0.013			0.044			0.200***			-0.065
			(0.059)			(0.059)			(0.059)			(0.059)
62-64			0.114			0.106			0.317***			0.014
			(0.115)			(0.111)			(0.106)			(0.105)
65-67			0.295			0.232			0.524***			0.124
			(0.195)			(0.187)			(0.181)			(0.180)
68-70			0.455			0.305			0.572**			0.141
			(0.299)			(0.291)			(0.278)			(0.268)
low qualification	-0.444***	-0.450***	-0.420***	-0.383***	-0.388***	-0.369***	-0.552***	-0.552***	-0.539***	-0.408***	-0.413***	-0.393***
	(0.035)	(0.042)	(0.039)	(0.035)	(0.042)	(0.039)	(0.033)	(0.041)	(0.036)	(0.034)	(0.041)	(0.037)
routine job	-0.367***	-0.362***	-0.389***	-0.296***	-0.292***	-0.309***	-0.535***	-0.535***	-0.548***	-0.313***	-0.308***	-0.326***
	(0.058)	(0.062)	(0.062)	(0.058)	(0.062)	(0.060)	(0.054)	(0.058)	(0.056)	(0.050)	(0.054)	(0.052)
Lives with partner	0.031	0.031	0.032	0.050	0.049	0.050	0.100***	0.100***	0.101***	0.087***	0.087***	0.088***
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.034)	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)
Good health	0.199***	0.207***	0.167***	0.214***	0.221***	0.194***	0.200***	0.200***	0.182***	0.157***	0.165***	0.137***
	(0.040)	(0.053)	(0.045)	(0.040)	(0.054)	(0.044)	(0.040)	(0.056)	(0.044)	(0.037)	(0.053)	(0.040)
Northern Ireland	-0.034	-0.035	-0.035	0.063	0.062	0.062	0.166**	0.166**	0.167**	-0.369***	-0.370***	-0.370***
	(0.081)	(0.080)	(0.083)	(0.084)	(0.083)	(0.085)	(0.074)	(0.075)	(0.075)	(0.085)	(0.085)	(0.085)
Wales	-0.177***	-0.180***	-0.162**	-0.234***	-0.237***	-0.226***	-0.139**	-0.139**	-0.131*	-0.288***	-0.292***	-0.279***
	(0.067)	(0.068)	(0.070)	(0.065)	(0.066)	(0.068)	(0.069)	(0.071)	(0.070)	(0.056)	(0.058)	(0.057)
Scotland	-0.048	-0.052	-0.032	0.009	0.005	0.018	0.129**	0.129**	0.140**	-0.199***	-0.203***	-0.188***
	(0.054)	(0.057)	(0.057)	(0.054)	(0.057)	(0.055)	(0.053)	(0.056)	(0.055)	(0.052)	(0.055)	(0.053)
_cons	0.186***	0.172**	0.203***	0.134**	0.122	0.135**	-0.349***	-0.349***	-0.297***	0.080	0.066	0.085
	(0.052)	(0.079)	(0.056)	(0.053)	(0.080)	(0.056)	(0.053)	(0.080)	(0.057)	(0.052)	(0.080)	(0.055)
N	4190	4190	4190	4190	4190	4190	4190	4190	4190	4190	4190	4190
AIC	11262.491	11264.129	11268.902	11531.770	11533.387	11539.676	11176.614	11178.481	11175.095	11398.528	11400.394	11405.805
BIC	11325.896	11333.874	11364.008	11595.174	11603.132	11634.783	11240.018	11248.226	11270.202	11461.933	11470.139	11500.912

Robust standard errors in parentheses; AIC and BIC from reduced form estimates; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Conclusions

This thesis has investigated three topics in the field of labour economics. In addition to its academic and policy interest, each chapter has analysed a theme related to a specific phase of the economic life of individuals: its beginning with school leaving, its maturity with unemployment scarring, and its end with retirement. The reminder of this section summarises the main findings of each chapter and briefly discusses policy implications and possible extensions.

Chapter 1 shows that an association exists between local labour market conditions and the school leaving decisions of 16-years-old British students belonging to a less affluent socio-economic background. In particular, we show that among students from home renting families, and especially from social housing, a positive correlation exists between the probability of enrolling in full-time post compulsory education and the local youth unemployment rate. Conversely, the probability of remaining in education tends to decrease with higher values of the local adult unemployment rate. The association is explained by arguments related to the opportunity cost of schooling, and to the discouragement caused by a fall in the expected return of education when adult unemployment is high. Factors such as parental tastes for education and social norms, which are associated with belonging to a higher socio-economic background, are likely to justify why students from better-off families tend to enrol into post-compulsory education irrespectively of labour market conditions.

Chapter 2 illustrates how unemployment experiences compromise the re-employability of British workers, a phenomenon known as "scarring effect of unemployment". Focusing on the last two decades, and in particular on the Great Recession, we find that unemployment scarring follows a counter cyclical pattern, with the estimated true state dependence shown to be larger during downturns. Job crowding arguments explain the counter-cyclicality of unemployment scarring.

The results also show that both in the early 2000s and during the Great Recession youths have been those affected the most by state dependence in unemployment incidence.

Chapter 3 investigates how retirement affects the cognitive abilities of British older workers. Consistent with the "use it or lose" hypothesis, the analysis suggests that retirement has a negative impact on the cognitive capital of both males and females as it worsens the natural age-related cognitive decline. Our findings also highlight the presence of heterogeneity in the negative effect of retirement across job types, with women performing routine occupations experiencing a significantly smaller retirement-induced decline in their cognitive functions.

The thesis allows some thoughts relevant from a policy perspective. Chapter 1 shows that the young people from a less affluent socio-economic background are not only less likely than youths from better-off families to participate in further education, but also more sensible to arguments related to the opportunity cost and the perceived returns of schooling. From a policy perspective, as labour markets recover following the Great Recession, measures should be implemented to keep education an attractive prospect among less socio-economically advantaged students. As well as from a reduction in the direct and the opportunity costs of post-compulsory education, participation among students from less affluent socio-economic background could benefit from interventions which raise the perceived return of schooling, such as information campaigns highlighting the real benefits of education. Promoting participation in further education among students from a less affluent family background would contribute to an increase in the stock of human capital in the economy, with beneficial effects both in terms of economic growth and social mobility.

Chapter 2 finds that unemployment experiences significantly compromise workers re-employability, especially during recessions. From a policy perspective, the finding implies that measures which cushion unemployment in short term are likely to be beneficial also for the longer term employment perspectives of workers. Moreover, as job crowding significantly affects employability during downturns, adjusting the public interventions in favour of the unemployed to the severity of the labour market conditions could be not only beneficial for the their short term well-being, but also favour better quality job matches and hence reducing the unemployment risk in the longer term.

Chapter 3 highlights the importance of maintaining a cognitively active lifestyle after retirement occurs. Given the correlation between cognitive functions and other dimensions of health, the benefits deriving from encouraging older people to take part in cognitively stimulating activities after leaving employment could extend well beyond their cognitive functions. Although more evidence is needed to frame interventions, such activities could be provided by local communities under the guidance of professionals in the field of cognitive functions.

The research contained in this thesis can benefit from a number of extensions. With respect to Chapter 1, the analysis could be extended by factoring-in the role of wages as well as that of unemployment rates. Additionally, policy interventions could benefit from a better disentanglement of the role of family aspirations from that of financial constraints in affecting school leaving decisions. The process is however complicated by the correlation between aspirations, family socio-economic background and borrowing constraints. Changes in family economic circumstances which do not affect family aspirations, or policy intervention such as modification of minimum wages for youths, could contribute to overcome the identification issues. The analysis contained in Chapter 2 could be extended by taking into account duration dependence as well as state dependence. The extensions would allow to better study the causes of unemployment scarring and, consequently, better inform policy interventions. Finally, the employment of panel data would improve the analysis contained in Chapter 3. Panel data would in fact allow making use of instrumental variables techniques additionally controlling for individual unobserved heterogeneity trough fixed effects.

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