Essays on the Impact of Information Communication Technologies on Human Capital

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Abstract

This thesis consists of three essays on the impact of Information Communication Technologies (ICTs) on cognitive, noncognitive and educational outcomes. Based on large social survey datasets, I find evidence of positive impacts of ICT use on subsequent developmental outcomes.

Chapter Two draws on the Longitudinal Study of Young People in England (LSYPE) data where I estimate the causal effect of personal computer usage by teenagers on their university attendance. A variety of matching methods aimed at minimising the differences of covariates between treated and control teenagers are applied, and show that access to personal laptop or computer increases the likelihood of university attendance, but these effects are heterogeneous.

Chapter Three uses the Millennium Cohort Study (MCS) to examine the impact of electronic games on cognitive and noncognitive skills in early childhood between the age of three and five. In the sample, around one-third of children did not play electronic games before the age of five. Using mothers' computer usage at home and new household internet access as instrumental variables, I find no evidence of a detrimental impact of playing electronic games but some evidence of cognitive benefits.

Chapter Four exploits the data from Survey data of Health, Ageing, and Retirement in Europe (SHARE), to examine the effect of internet use on the cognitive decline of retirees. The casual impact is identified by instrumenting current internet use with the past career and occupational information of the retirees who, in these surveys, started their working life before the large-scale computerisation at the workplace after the 1980s. The results demonstrate that ICT usage slows the rate of cognitive decline among retirees, and the decline is not primarily driven by advantaged groups.

To my beloved parents.

Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. I declare that chapter four is a collaboration with Prof.Colin P. Green and Dr.Vincent O'Sullivan, and both agree that I have completed over 70% of the work on its current version. Apart from chapter four, I confirm that other chapters have been solely results of my own work.

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Acknowledgements

To my parents who have been doing the utmost to support me in all these years, both mentally and financially. Thanks to my mother for her selfless devotion to our family, for bringing a joyful and caring life. Thanks to my father for setting a model of responsibility and integrity. I owe them a lot as I have been far away from them for more than seven years and determined to study economics instead of working in a bank. I may have taken one road less travelled by and less expected by my families, but I believe that has made all the difference.

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Finally, I dedicate this thesis to myself, to this journey of reducing my aversion to many modern technologies. I wish this thesis not the end to my academic thinking. I wish the last sentence is not only a wish.

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Chapter 1

Introduction

Since the invention of the first personal computer and internet in the 1980s, the world has witnessed a significant change in our capacity to communicate and share information via a range of Information Communication Technologies (ICTs). ICT is a broad term that includes all devices related to computer, internet and digital technologies such as mobile phone, digital TVs and other communication devices. The family of ICT is still expanding with technological innovation that has introduced wireless network, artificial intelligence, and cloud services *etc.* The rapid advancement of ICTs has increasingly changed how people work, learn and live, in the sense of enhancing the connection and speed.

There have been long-standing discussions over the impact of ICTs on human capital, at all levels and in both formal or informal settings. Governments and schools have paid great attention to both ICT learning and investment in school education. For example, ICT has been integrated into the school curriculum for all pupils from five to sixteen in maintained schools since the Education Reform Act of 1988 in the UK. Later in 1999, the New Opportunities Fund was launched and provided 230 million pounds to train more ICT-skilled teachers.

The relevant research can be divided into two streams. One evaluates the effectiveness of school ICT investment such as computer access (Angrist and Lavy, 2002(5)), ICT funding (Goolsbee and Guryan, 2006(60); Machin *et al.*,2007(83), ; Leuven *et al.*,2007(78)), computer-assisted learning programs (Banerjee *et al.*,2007(10); Barrow *et al.*,2009(12)) - mostly in an experimental or quasi-experimental setting. Another stream investigates whether home ICT access or use contributes to better educational outcomes (Schmitt and Wadsworth, 2006(105); Malamud Pop-Eleches *et al.*, 2011(84); Fairlie 2005(45), 2010(46), 2012(48), 2013(49); Fiorini 2010(52); Faber *et al.*,2015(44)). Among these streams, the results are mixed and often statistically insignificant on standard educational outcomes. Nevertheless, there are some findings of positive impacts on cognitive, noncognitive or ICT skills (Fiorini 2010(52); Malamud Pop-Eleches *et al.*,2011(84)).

Outside of school, ICTs are also considered to play an important role in enhancing people's well-being by boosting entertainment experience, facilitating routine tasks, and offering flexible information exchange. Younger generations such as the Millennials and Generation Z, have experienced increasing immersion in ICT and a variety of social media in their daily life. Research and policy concerns centre on the impact of TV and electronic games on children's cognitive and social development. Many experiment-based studies have emerged in the field of the psychology and health sciences, and provided evidence of both the positive and negative side of the ICT use. For instance, electronic games are found to be associated with worse outcomes in externalising, attention and emotional problems, but also improved pro-social behaviours and creativity (see the discussion by Ferguson 2015(51)). Relevant studies in economics exploit large social survey data and suggest some positive impacts of video games on cognitive performance rather than any significant detrimental impact on noncognitive aspects (Fiorini 2010(52); Suziedelyte 2015(7)).

Many discussions so far have tended to focus on children and adolescents who are more active ICT users. Meanwhile, mature adults are often paid attention to how technology switched their labour skills and wage structures in labour market (e.g.Autor *et al.*,1998(8); Doms *et al.*,1997(37)). However, ICTs still matter in daily life and have the potential to improve social life and life-long learning (e.g.Lelkes *et al.*,2013(76); Selwyn *et al.*,2004(107)). Among the elderly, computer and internet are increasingly suggested as helpful in protecting the elderly from negative feelings of social isolation or cognitive decline (Lelkes *et al.*, 2013(76); Litwin *et al.*,2016(82).

The overall goal of this thesis is to investigate how people are affected by evolving modern ICTs. Within this broad topic, I have devoted my efforts to examine the impact of conventional ICTs, computer, electronic games, and the internet, on individual cognitive, noncognitive and educational outcomes using large social survey data from the developed countries. Notably, the samples analysed in this thesis covers three representative cohorts and life periods: the youth born in the 1990s, the early generation grew up with computers and the internet in their homes. Then it is the millennium cohort children with greater access to digital devices in their early childhood. Finally, the elderly group, born in the 1950s on average, has spent more time in an era with limited experience of modern electronic products. These three groups have distinct features in their interactions with ICT in daily life. Teens usually have more flexible ICT use for diverse purposes that mix with learning, socialising, and multiple forms of entertainment. While young children at home use ICT mainly for an entertainment purpose before a more mature cognition develops. The elderly, less embedded with modern technologies in their main lifetimes, are usually performing basic operations on ICT devices. Therefore, the three empirical essays in this thesis provide essential insights into the heterogeneous impact of ICT on these different segments of the population.

Reliable empirical research on a causal effect largely hinges on addressing the issue of endogeneity in ICT use. To illustrate, children confronted with more peer or emotional problems may be more likely to play computer games as an escape from the real world, which leads to an overestimated impact of gaming on noncognitive performance in naive regressions. Likewise, the elderly with lower cognitive and well-being level might be more reluctant to use ICTs because of potential higher mental learning costs. These selection issues generate obstacles in estimating unbiased causal impacts of ICT use. Moreover, some latent personal traits such as openness and extraversion might affect cognitive development and one's preference for ICT use simultaneously, bringing ambiguous bias to empirical estimation. In this thesis, I have adopted a range of approaches that help with isolating the causal impact of ICT on human capital development at three distinct life stages.

Chapter Two seeks to estimate the effect of personal computer usage by teenagers on their university attendance using the Longitudinal Study of Young People in England (LSYPE) data which follows the lives of over 15,000 people in England born in 1989 and 1990. Around half of teenagers report the ownership of their own computer or laptop around age 17 but only around 10% have one before age 14. This chapter investigates the impact of this new purchase as one educational input, which differs from prior research on general ICT investments at family or school level. The treatment here is exclusive to the young people themselves, and a home setting allows further consideration for relevant behaviours to explain ICT effectiveness at an individual level.

In the absence of exogenous variation in personal computer use, I rely on a variety of matching based methods aimed at minimising observable (and through this unobservable) differences between treated and control teenagers. I find that receiving a personal laptop or computer increases the likelihood of university attendance at age 18 or 19. Further, taking account of ICT-related behaviours, often suggested as mechanisms through which ICT may affect educational outcomes, does not substantially change our results: the impact of having a personal laptop or computer is around two to three percentage increase in the likelihood of attending university in the first year after high school. The results survive a range of robustness tests on potential selection on unobservables.

In Chapter Three, the attention is placed on young children aged between three and five years old - a crucial period in human capital development as suggested by much economic literature. It links to the growing literature of early children development that has primarily focused on evaluating programme that take many forms such as improving childcare curricula, modifying parental habits, and providing relevant education or training. Not much research looks into children's own leisure activities or time allocation. In addition, corresponding psychological research tested the impact of short-term exposure to video games on cognition or brain functioning, and primarily centred on adolescent samples. This chapter provides the first study in the economics literature in addressing the causal relationship between electronic games and early children development in both cognitive and noncognitive development.

I use the Millennium Cohort Study (MCS) to examine the impact of playing electronic games on both cognitive and noncognitive skills among a cohort of children born across England, Scotland, Wales and Northern Ireland in 2000-2001. This follows from concerns that the increasingly popular video games may be harmful to young children, particularly in terms of emotional development that might be negatively influenced by violent games. The MCS provides a useful setting as it surveys young children in a period before electronic devices, such as smartphones and tablets became ubiquitous in homes. In our sample, around one-third of children report no electronic games playing at home at a time when nearly 80% of households have an internet connection. The primary instrumental variables for identification, more related to ICT access, are mother's computer usage at home and new household internet access. In addition, heteroskedasticity-based identification and the Conditional Mixed Process (CMP) methods are implemented to improve statistical inference in the presence of endogeneity. I find no evidence of a detrimental impact of playing computer games on noncognitive skills but some evidence of positive impacts on cognitive development.

The prevalence of ICT is also increasing gradually among the older population who may benefit from improved social-engagement and cognitive functioning. In an ageing society, it is of policy interest to evaluate whether ICTs have the potential to enhance the life quality of the elderly. Chapter Four goes beyond previous correlational studies in gerontology and psychology about how technology affects the well-being of older people. Most existing literature presents results from experiment-based studies that often recruit a small sample of participants and investigate the potential impacts of specific ICT interventions. In parallel, researchers also focused on the distribution and determinants of ICT use among the older population to discuss the digital divide between age and cohort groups. Against this background, this chapter adds to increasing studies based on more recent large social survey data, with a particular contribution in a causal identification.

We exploit the Survey of Health, Ageing, and Retirement in Europe (SHARE), a large cross-national longitudinal dataset, and provide consistent evidence of the positive impacts of a digital inclusion among the elderly. In particular, the sample has been restricted to retired people with consideration for removing the effect of retirement on cognitive performance. To establish a causal impact, our identification approach is to instrument current internet use with past career and occupational information of the retirees. The idea is that individuals who in these surveys started their working life in the 1970s were exposed to different levels of computer technology due to the uneven spread of computer technology in workplaces from the 1980s to present. The results demonstrate that ICT usage slows the rate of cognitive decline among retirees, and groups from advantaged backgrounds do not drive such a positive impact.

Chapter 2

Does Personal Computer Increase University Participation ?

2.1 Introduction

Over the last two decades, there has been a dramatic increase in the use of Information Communication Technology(ICT) around the world. In the US, the home computer access rate increased from around 50% in 2000 to over 80% in 2012[1]. In the UK in 2007[2] , over 90% of teenagers had access to a home computer. The use of computers is also ubiquitous in the education system. Governments and schools have made substantial investments in ICT for educational purposes. For instance, the US federal communication commission(FCC) spent more than two billion dollars as one commitment to the Telecommunications Act of 1996, with the aim of providing better connection services. The UK government doubled the ICT expenditure in secondary schools between 1998 and 2002. While in 2008, England provided free computers to nearly 30,000 low-income families at a total cost of 194 million pounds through the Home Access Programme.

Given this increase in availability, it is of great policy interest to understand the effectiveness of this investment in human capital development. There has been a longstanding debate about the role of technology in education. As discussed by Postman(1990)(98), frequent ICT upgrades might be accompanied by many changes in educational models, learning habits, and even brain functioning as people are increasingly exposed to a variety of electronic devices. The existing literature that evaluates the impact of ICT investment on academic outcomes reports mixed results. Many cross-sectional studies have documented a positive association between ICT investment and various educational outcomes(Attewell and Battle 1999(94); Fairlie 2005(45),2010(46); Schmitt and Wadsworth 2006(105)). While, some experimental evidence is supportive of the benefits of specific Computer Assisted Instruction (CAI) on test scores, especially improvements in maths (Banerjee *et al.,*2007(10); Barrow *et al.,*2009(12); Carrillo *et al.,*2010(24)). However, other studies suggest that ICT-assisted learning may have a limited impact on enhancing school performance, despite the efficient and flexible learning environment that technology enables. (Angrist and Lavy 2002(5); Leuven *et al.,*2007(78); Goolsbee and Guryan 2006(60)). Several experiment-based studies exploit exogenous variation from policy change (Machin *et al.,*2007(83)), public programmes (Shapley *et al.,*2010(109); Malamud and Pop-Eleches 2010(84)) and designed experiments(Fairlie *et al.,*2012(48), 2013(49)), and find little evidence of a positive impact of ICT investment. The absence of a significant impact in these rigorous studies may reflect the underlying mechanisms through which ICT could improve or worsen educational outcomes: ICT can manifest its importance in providing students with more flexibility; however, other ICT-based activities such as video games and online-networking may displace constructive activities.

This paper provides new evidence of the impact of home ICT investment on educational outcomes using a large longitudinal dataset in the UK. Different from general ICT investment at school or household level, this study focuses on the relationship between a specific form of ICT, i.e. personal laptop or computer, individual usage, and educational performance. The analysis draws on data that includes many demographic controls for computer usage and other individual behaviours. The nature of the large longitudinal dataset helps address the common concern about small sample inference in RCTs and provides insights from a more general population.

The critical issue in the identification of the impact of ICT investment on education is the endogeneity of ICT investment and usage. For instance, we are likely to observe a positive association between home ICT and university attendance if students receive their personal computer as a reward for good school performance. Furthermore, there is ambiguity in how students with different characteristics would use their ICT devices. It would seem that some students indulge in computer games rather than information searching and learning. Conversely, some students may use technologies more effectively with the help of parents and relevant training at school. As an attempt to mitigate these concerns, I employ a matching approach to estimate the treatment effects of a personal computer on educational outcomes. With less parametric dependence, observations can be compared in a "simulated" environment of randomisation that is created by the matching procedure. I acknowledge that matching estimation of treatment effects rests on the Conditional Independence Assumption (CIA), i.e. no relevant unobservable once matching on observables occurs. Bias arises if there are unobservable variables that affect treatment status and outcome. As robustness checks, I test the sensitivity of estimated results to changes of various confounders using bounding and simulation methods.

I consistently find a positive impact of having a personal computer on the probability of going to university: an increase by a magnitude of around three percentage points. Moreover, results suggest gender differences and an inverted-U shape of the treatment effect. The results are robust to several attempts of violation of the Conditional Independence Assumption(CIA) and a range of alternative matching approaches. This study does not claim to measure all potential factors that affect ICT effectiveness, but I do find evidence of the positive impact of constructive computer usage (doing schoolwork) when other related behaviours are taken into account.

The remainder of the paper proceeds as follows. Section two provides a more detailed review and discussion of the literature. Section three and four illustrate the main identification strategy and the description of our dataset. Section five presents results about the main treatment effects, heterogeneity and the underlying mechanism from the perspective of behaviours. Section six tests the identification assumption and the final section concludes.

2.2 Literature Review

2.2.1 ICT at School

There is an extensive literature that examines the impact of school ICT investment on academic outcomes such as high school graduation rates, courses passing rates, and school grades. A standard approach is to add ICT investment to a standard model of education production. One prominent form of such digital investment is Computer Assisted Instruction (CAI) that enables more individual and flexible self-learning by providing students with specialised programmes on computers in the classroom. This advantage can be theoretically modelled as time allocation in class: benefits come from the supplemental instructional time in a day at school for students who may face limited direct instructions from teachers. Barrow *et al.*(2009)(12) discussed CAI effectiveness from this perspective and found empirical supports that the treatment effect of CAI is positively associated with the class size.

Banerjee *et al.*(2007)(10) evaluate one "Computer-Assisted Learning" programme implemented by a large NGO named Pratham in India[3]. Trained instructors from the local community provided children with two hours of shared computer time per week (two children shared one computer), one hour during class time and one hour either immediately before or after school. During that time, the children played a variety of educational computer games which emphasised basic competencies in the official mathematics curriculum. Through random sampling and comparison, the authors find a statistically significant effect on math scores - an increase of 0.47 of a standard deviation. Carrillo *et al.*(2010)(24)also provide similar evidence that an Ecuadorian program of three-hour individualised instruction increased mathematics test scores by around 0.30 of a standard deviation. However, Angrist and Lavy (2002)(5) find different results by exploiting a lottery-based sponsorship in Israeli State.[4] Based on a survey of teachers, they discover consistently negative and only a marginally statistically significant relationship between the CAI intensity and 4th-grade math scores. In addition to CAI, other practical investment in the form of hardware has also received a great deal of attention from researchers. By employing a difference-in-difference method, Goolsbee and Guryan (2006)(60) exploit the case of the Federal E-subsidy in internet and communication in California schools and find zero impact of the internet expansion on students' academic performance. Similar evidence is provided by Leuven *et al.*(2008)(78) who evaluate a subsidy policy in the Netherlands.

Overall, these diverse results seem to cast some doubts on ICT effectiveness in practice. For one thing, it is somewhat expensive to develop tailored programs for CAI, and it may not efficiently enhance general academic performance. Up to now, there have been only a few specific CAI programs[5] provided for experimental purposes on a relatively small scale. CAI itself is still controversial in a way owing to a lack of strong theoretical basis (Stoll 1995(115)). The potential impact of CAI may take time to develop in the long term but be disruptive in the short term (Angrist and Lavy, 2002(5)). It is also ambiguous how policies and programmes are implemented when they are confronted with difficulties in practice[6]. In addition, general public ICT investment requires compatible teaching skills and other school inputs. Any benefits of ICT-enhanced learning cannot stand out alone without support from relevant curriculum and class arrangement that achieve a better balance between conventional methods, which is primarily determined by teachers and schools. This problem is illustrated and discussed in the study by Fuchs and Woessman (2004)(123) who show that the simple bivariate correlation between computer access and academic performance becomes small once many other school characteristics are controlled for. Finally, the inherent difficulty of controlling for endogenous reactions to these investments poses a threat to convincing causal inference.

2.2.2 ICT at Home

In comparison to the amount of research on ICT in schools, there has been little research into the educational impact of home ICT investment. This parallel line of literature differs fundamentally concerning who makes the investment decision and how ICT is used. For one thing, both parents and students can take part in the decision regarding ICT purchases. Home ICT investment is endogenously determined in the sense that people buy ICT for different reasons such as entertainment, work, education, or some combination of these. Compared to the main educational purpose of school ICT, these reasons are more complex and are likely to be more closely correlated to individual and household characteristics. It is also different from general ICT operations and instructions at school; students typically have more choice and autonomy in their home ICT usage.

Empirically, cross-sectional studies typically show a positive association between computer ownership at home and students' achievement (Attewell and Battle 1999(94); Judge 2005(72); Jackson *et al.,*2006(69) *etc*). Using two major US panel datasets[7], Fairlie *et al.*(2005(45), 2010(46)) find a strong correlation between home computer access and various school performance measures such as grades, graduation probability, and suspension. After controlling for typical home environment factors and extracurricular activities, the results hold across several estimation methods[8]. More recent work by Vigdor *et al.*(2014)(121) shows a modest but a consistently negative impact of home computers on math and reading test scores in a value-added model. The authors highlight the contrary results from within and cross-student specifications and suggest that ICT access can be more detrimental to students from disadvantaged backgrounds.

The main identification problem is that home ICT availability and usage is non-random. This has led to a number of different approaches aimed at providing credible causal estimates. Fairlie(2012)(48) conducted an experiment by providing free computers to around 150 low-income community college students for home use. The point estimates are consistently positive across different measures of educational outcomes but are substantially smaller than the comparable cross-sectional estimates in magnitude, which suggests positive selection in computer ownership in cross-sectional data. With a larger sample and different targeted subjects, similar experimental research conducted by Fairlie *et al.*(2013)(49) finds different results: null effect of the home computer on any educational outcomes of schoolchildren. Detailed follow-up surveys further suggest the absence of a positive treatment effect from various types of computer usage. With direct relevance to public policy, Malamud *et al.*(2011)(84) employ a discontinuity design to evaluate a government program that allocated vouchers to purchase computers to low-income children in public schools in Romania. The results show some enhancement of cognitive and computer skill, and this contrasts with a consistently negative impact on GPA and math scores of between 0.2 and 0.5 standard deviations.

Using data from the British Household Panel Survey (BHPS), Schmitt and Wadsworth (2006)(105) find a positive association between home computer ownership and the number of A-level passes and GSCEs, conditional on a variety of individual, household and area characteristics. In this correlational study, the OLS and logit estimates of PC impact on subsequent educational attainment hold positive when future computer ownership or other household assets are controlled for as proxies for unobservable characteristics that might affect computer ownership. To better control for confounders, Machin *et al.*(2007)(83) use the fact that a new rule in 2001 transformed the allocation of ICT funds to Local Education Authorities(LEA)[9]from a bidding process to a population-density-based one. This change was aimed at making the allocation more equitable and created “winners” and “losers” among LEAs. By implementing a difference-in-difference strategy, they find evidence of a positive causal effect of increased ICT funding at LEA level on educational performance among primary school students. The positive impact is statistically evident in English and science where there is a higher frequency of ICT-based teaching, but not for mathematics. Unlike many researchers suggesting a positive impact, Faber *et al.*(2015)(44) report a zero effect of upgraded broadband speed on educational outcomes among a wide range of UK students. The exogenous variation of the ICT upgrade comes from a different distance to telephone exchange stations that are fixed by districts. The broadband variation among households around over 20,000 boundaries is statistically significant, generating discontinuous jumps in the available internet capacity. The average jump suggests approximately 20 to 50 percentage reduction in download times but does not affect key stage test scores.

2.2.3 Behavioural Explanations

There have been attempts to examine the mechanisms through which ICT may affect student outcomes by separately regressing a set of related behaviours on a treatment. The insignificant impact on educational outcomes might be explained by different competing behaviours, which has been suggested as a maximisation problem of time allocation (Vigdor *et al.,*2014)(121). For instance, the distraction from computer games might dominate and leave less time for constructive activities such as paper reading (Malamud *et al.,* 2011(84); Beuermann 2013(15)). However, Fairlie *et al.*(2013)(49)) find no change in homework time among students who were allocated a home computer. In some cases, the introduction of home computer technology is even associated with more time spent on homework but negative impacts on school performance, which implies reduced learning efficiency (Vigdor *et al.,*2014). In addition to computer access, computer-relevant behaviours are seemingly less affected by ICT investment such as broadband speed(Faber *et al.,* 2015(44)). Nevertheless, empirical evidence suggests the benefits of flexible learning for university students as the positive impact is more substantial for students living far from campus (Fairlie 2012(48)).

The above results demonstrate the potential complexities of behavioural responses to ICT investment. There is a reason to suspect that these mixed results are affected by measurement error in many of the behavioural variables. Also, it is possible that these behaviours are inherently persistent among students and they reflect another dimension of characteristics. Consequently, it is worth adding ICT-relevant behavioural controls in regressions of educational outcomes. Relative to existing literature, this paper seeks to provide a causal estimate for the effect of a home computer on the development of schoolchildren, with further consideration for related behaviours as an attempt to disentangle competing effects.

2.3 Methodology

Before turning to empirical estimates, I first consider a basic equation of educational outcome that illustrates the potential impact of ICT investment:

$$Y_i = \alpha + \beta_1 D_i + \beta_2 X_i + u_i \ (2.1)$$

where Y_i is a variable measuring individual i's educational outcome; D_i is a dummy variable and takes the value one if the individual receives the treatment of ICT investment. X_i is a vector of individual and household controls. u_i is the error term that includes unobservable characteristics and other disturbance factors.

The identification of the impact of ICT investment might be hindered by endogeneity from a range of different sources, if the error term u_i is unlikely to be orthogonal to explanatory and outcome variables. First, selection bias arises because individuals and households with particular characteristics have a higher probability of buying a personal computer and preparing for university. Causality may run in the opposite direction when parents buy computers as rewards for children's good performance, which is more evident in home ICT studies and would bring upward bias in estimated treatment effects. Second, students and parents may respond to the treatment. Downward bias might come from the unobserved displacement effect on other essential inputs such as learning effort, parental monitoring, and assistance when there is no guarantee of the improved efficiency as a result of digitalisation. It is also likely to see bias in the opposite direction if the treated are further motivated in some way.

Our initial approach to these problems is to apply Propensity Score Matching (PSM). PSM attempts to balance the assignment of treatment to research subjects that are often not random in observational data - going some way to overcome the fundamental selection problem. Moreover, its non-parametric feature contributes to a precise estimation of treatment effects and it fits our research particularly when there is insufficient knowledge about the structural impact of ICT as an educational input. With less model dependence, we can obtain the Average Treatment Effect on Treated (ATT) as the mean difference in the outcome of the treated and controls over common support range, conditioning on relevant covariates.

In our setting, the outcome variable Y_i equals to one if the respondent i is studying for a university degree at age 18 or 19. The treatment D_i about ICT investment has been restricted and specified as the new purchase of personal computer between age 15 and 17. I exclude those respondents who reported to have their own personal computer already at age 15. So the control group is the students who never have an access to their own computer or laptop before age 17. The primary balancing score is the propensity of receiving the treatment, which possibly is the most developed and popular strategy (Pearl 2010(95)). Formally, the average treatment effect of interest is the ATT that can be specified as:

$$\tau_{ATT} \equiv E(Y_1 - Y_0|D = 1) = E_{[p(X)|D=1]}[E(Y_1|p(X), D = 1) - E(Y_0|p(X), D = 0)]$$

The propensity score $p(X)$ is the probability of receiving the treatment and is estimated from a logit or probit model:

$$P(D = 1|X) = \gamma X + \epsilon$$

X is a set of observable covariates including not only demographic variables such as ethnicity, gender, parental education, family income and family social economic class(SEC), but also measures of school quality and performance as well. γ is a vector of corresponding coefficients. ϵ is error term. It is impossible to observe the counter-factual: the same subject before and after treatment. Thus, it is crucial that we have properly selected comparable participants based on observables that are independent of treatment status. That being done, the treatment effect can be identified without confoundedness. Formally, propensity score matching (PSM) requires $Y(0), Y(1) \perp D|P(X)$. In addition, common support is imposed to ensure positive probability of being treated and controls (Heckman *et al.*,1999(65)), which is written as $0 < P(D = 1|X) < 1$. This rules out the possibility of perfect predictability of D given X.

One central issue in successfully implementing matching is to appropriately select covariates and the matching algorithm to achieve a good balance between bias and efficiency. In our specified model, these covariates X cover many household characteristics that are either fixed over time or measured before a student receives the treatment. Further, it is suggested to make a theory-driven selection and to consider data availability and reliability: only variables that influence the participation decision and outcome simultaneously should be included (Caliendo and Kopeinig 2005(20)). In our data, many basic variables are quite balanced between treatment and control groups. In the baseline, I include demographic variables and family background, which are commonly used in specifications of education production functions. The school quality and students' school performance (self-reported) are taken into account on the ground of their performance-based selection into having a personal computer. Further, the "smoking" indicator for risky behaviours could reflect some non-cognitive aspects such as self-control. Parents' involvement in the young respondent's school life helps control for other intangible family investment and disciplinary impacts on computer usage. Although many other variables such as the attitude towards university and ICT can be influential, they might be highly correlated with the outcome and current status of ICT use, and seem less clear as other baseline covariates. I, therefore, test them as potential confounders.

In the absence of an absolute "winner" or "loser" between different methods, another key issue is to determine a matching algorithm that is mostly dependent on the data structure in practice. Our large sample drawn from a broad social economic background contributes to better matching in terms of many observable characteristics. Essentially, I implement different methods and chose the radius matching for its relatively superior matching quality in our sample.

Indeed, the matching estimation of treatment effects is based on the Conditional Independence Assumption (CIA) that excludes simultaneous impacts of unobserved variables on the treatment assignment and outcome determination. Clearly, it is hard to test this strong assumption in practice directly. In my analysis, I check it indirectly by showing how the estimated treatment effects change in response to simulated confounders. If the estimated effects are sensitive to possible deviations from the unconfoundedness assumption, our approach is called into question.

2.4 Data

Our sample is drawn from the Longitudinal Study of Young People in England (LSYPE)[10]which follows a cohort born in 1989 or 1990 in England. The first survey took place in 2004 when the sampled young people were aged between 13 and 14. These children and families have been interviewed through various forms such as face-to-face or telephone interview and self-completion (for waves one to four)[11] . The first wave collected information from over 15,000 households, and the sample size is over 10,000 in the first five waves. In addition to detailed demographic descriptions, there is a range of information regarding students' leisure activities(reading, clubs, sports *etc.*), risky behaviour (smoking, drug use *etc.*) and self-reports on school quality, facilities, and students' academic performance. Information about family background is provided by the main parent who is identified as the person most involved in young person's education.

The working sample in this paper consists of people who have participated all the first, second, fourth and sixth waves, excluding the boost sample in wave four. The treatment status is characterized using relevant measures in waves two and four. All pretreatment covariates are taken from the first wave. This cohort could first started higher education in September 2008, which is documented in wave six. The total number of full responses (both parents and young people) is 13,914 in the first wave and then is reduced by near 40% to 9,799 in the sixth wave.

2.4.1 Computer Access and Usage

The respondents were first asked about home computer access at age 13 and 14, and over 80% of them have access to a home computer, which is consistent with the high home computer access reported by parents (87.9%, see Table 2.1).

In the second wave, young respondents were asked whether they had a computer that could be taken to school at age 15. Only 11% of young pupils reported such an access. Nearly 80% of respondents had to share a home computer with parents or siblings. Later at age 17, they reported whether they had their own laptop or computer that excluded those of any other people in the household. The proportion of computer owners increases to approximately 56%. This highlights variation in the ownership of personal computer between age 15 and 17.

The use of ICT activities variables are mostly reported between the age of 14 and 15 in the first two waves and covers both home and school aspects of use. Only 0.6 % of young respondents reported no use of computers anywhere at age 14. Home computer usage can be divided into school-work use and non-school use. Conditional on having access to a home computer, half of the respondents spent 1-2 days using a home pc for school work through most basic operations such as word processing and web searching. Only 17.4% of respondents used other computer packages for learning purposes. By comparison, the dominant computer usage for non-schoolwork was playing games (73.9%), music listening (65.9%) ranked the second. Less than half of the teenagers mentioned online social activities (32.1%) or web searching (43.7%) at the age of 13 or 14, but the usage increased one year later. For ICT usage at school, respondents were asked about the number of days a week when they use computers in ICT or computing lessons that teach computer operations and related knowledge. Over 70% of respondents reported 1-2 days spent on these ICT-relevant classes, but the proportion is only around 40% for computer usage in other classes. Around 40% reported “less than one day” or “never”. The frequency of computer usage at school increased to an average of 3-4 days one year later, higher than the average 1-2 days in an earlier wave. This is also compatible with the increasing computer usage at home. Nearly 90% of young respondents expressed their feelings about the importance of computers in helping their school performance, and over 80% of students consider themselves at least fairly good at ICT subjects, although less than half expressed great interest in ICT.

2.4.2 Educational Outcomes

The outcome variable of interest is university attendance at the age of 18 or 19. The respondents reported a range of current activities including whether they are currently doing a course at a university, or going to school/college, or doing any job. They were asked many questions about courses or qualifications they were studying, learning aims, and if they were at university or not. Participants were asked about the university they are attending in waves six and seven. Among all 9,799 participants in wave six, 33.74% were currently at university and this proportion goes up to 44.85% in wave seven. I use the derived variable of "the highest qualification studied", which took the young person's responses to a range of qualification variables, as well as the derived variables about A/A2/AS levels and GSCEs qualifications being studied at wave six to determine the highest level of qualification being studied by the young person. There are a small number of cases revised to the category of "other" due to insufficient information. This outcome variable focuses on the successful university attendance in the first year after high school, and does not capture the drop out from the university afterwards. Also, it may provide insufficient information about more detailed status at each key stages of university application. Overall, the main outcome measure provides a general measure of HE participation and may be limited in picturing students' heterogeneous decisions over universities. The university attendance rate, conditional on application, however, is around 80% in our sample and suggest less a problem of the unmatching between initial application and later attendance in our main analysis.

Finally, the working sample includes 3,128 students who were studying for a degree among 9,538 observations at the age of 18 or 19. Jake Anders (2012)(3) points out a high level of non-response for these university outcome variables and an over-report of higher education (HE) participation in LSYPE, in comparison with other administrative datasets[12]. There could be various sources such as initial high non-response rate, different definition of HE participation and attrition bias. Bearing these on mind, it might be better to interpret our precise estimates more conservatively in terms of a nationally representative sample. Nevertheless, LSYPE is still one informative and important dataset to further the understanding of HE access in England (Jake 2015(3)).

2.5 Results

2.5.1 Propensity Score Estimation

The basic idea of matching is to find a group of non-participants that are similar in a range of covariates that capture pre-determined characteristics. Our preferred specification contains information about annual family salary(standardised), social economic class (SEC), parents' highest education qualification, home computer access, and individual controls that are commonly used in regressions of educational outcome. The estimation of propensity score is based on a linear form of all covariates since our data have achieved balance without the need to adding quadratic or interaction terms that are common modifications in practice.

As shown in Figure 2.1, the estimated propensity score is clustered around an average of 0.565 and is identified as five blocks, ranging over 0.395 and 0.713 under common support. Only six observations are dropped due to failing the common support condition. Gender, ethnicity and school performance are the most significant predictors of treatment status, with an average marginal effect of 0.065, 0.052 and 0.031 respectively. The density plot of the propensity score (Figure 2.4) shows that the treated group has a higher probability; their means are significantly different by a quarter of a standard deviation, suggesting a bias of 8.1%. The result indicates positive selection into ICT investment in our sample. Overall, our sample shows a relatively balanced distribution of propensity scores, which might be attributable to our treatment that has restricted the ICT investment as new purchase between age 15 and 17. In other words, students with an intense desire for ICT tend to acquire their own computer already before age 15. This excludes the cases of very high propensity score and leaves our sample with an average preference or desire for ICT purchase. In the absence of an overly skewed propensity score distribution, I can match more comparable observations and obtain better results.

2.5.2 Effects of ICT investment on University Participation

I now use the PSM approach to estimate the effect of ICT on university participation. The main results for a series of increasingly complete specifications are shown in Table 2.2. The treatment effects are consistently positive and statistically significant at the one percent level. The estimating sample reduces to around 7,000 due to dropping those observations who reported always or never having one computer.

The first six columns present results from logistic regressions. The first column demonstrates the unconditional relationship between ICT investment and the probability of attending university - the average marginal effect is 0.036 at a significance level of 0.01. The 95% confidence interval of the effect is 0.015 to 0.058. The estimate implies that having a computer is associated with a 3.6 percentage higher probability of attending university at age 18 or 19. The treatment effect increases to around 0.040 when more control variables are included. Controls for family background do not reduces the estimates much, but the indicator for smoking further reduces the average treatment effect by 15% to 0.034. Including the self-rated school-performance likewise reduces the treatment effect to 0.029. In brief, the underlying conditional relationship is not influenced markedly by including controls for apparent confounders.

The PSM estimates of the treatment effect do not differ markedly from the logit specification and show an increase of 0.030 in university attendance, approximately a 10% increase of the average level from 0.328 to 0.358. This implies that the teenagers who received their own computer between age 15 and 17 are around three percentage points higher in the likelihood of studying for a university degree at age 18 or 19. This estimate is smaller than the 6 to 8 percentages points by Fairlie *et al.*(2010) who use similar National Longitudinal Survey of Youth (NLSY97) in the US.

It is worth noting that the treatment effects in matching are only defined in the region of common support, mainly between 0.3 and 0.7 in specification (7) to (9). In the preferred specification (7) with full covariates, there is a substantial overlap between the treated and controls and only four observations are dropped because of the common support restriction. For that reason, only a small difference exists and this is negligible if we compare results with that in specification (8) using an untrimmed sample. Additionally, the estimates are less sensitive to the choice of a logistic or probit specification at the first stage. In sum, all of the estimates I have presented so far demonstrate that having one's own computer increases the likelihood of attending university afterwards, conditional on valid CIA. Using matching methods, I account for the selection into ICT purchase and reduce the original bias by around 90%. As shown in Figure 2.3, the standardised bias of all the observable covariates is less than 3% after matching, implying reasonable comparability between the control and treatment group in our estimation.

2.5.3 Impacts of Behaviours on ICT Effectiveness

2.5.3.1 Behavioural Variables: Principal Components Analysis (PCA)

Having established a positive relationship between personal computer and university participation, I now seek to provide evidence of potential behavioural mechanisms. Previous literature has attempted to investigate the mechanism of ICT investment via testing students' behavioural responses to ICT investment but in practice shows contradictory evidence. Direct inclusion of behavioural variables into our main regression may give rise to identification problems because of unknown inter-correlations among relevant behaviours. For instance, students may potentially substitute between various activities due to time constraints. Furthermore, these choices may be related to underlying behavioural patterns and individual preferences. From this aspect, students' behaviours are less likely to be affected by ICT investment, as is suggested by the current literature. Motivated by time allocation theory (Vigdor *et al.,*2014(121)) and current empirical results, I use principal component analysis (PCA) as an attempt to disentangle several activities and construct behavioural variables. Despite the existence of unknown inter-correlations, several components of relevant behaviours can be extracted. A further statistical process such as variance-based rotation not only ensures the orthogonality among various behavioural variables but amplifies the underlying variance as well.

I include the most frequently discussed activities: playing computer games and doing homework, as two representative sources of competing impacts. Reading behaviour is also taken into account as suggested by literature for its potential relationship with learning habits and cognitive development. School ICT usage is also taken into account. To implement the data-driven method, I select consistent measurement of these behaviours at different times since the underlying variance analysis can be sensitive to the measurement scale. It is possible that these behaviours are intercorrelated as substitutes or complements. Principal component analysis (PCA) takes advantage of all the variances of factors and subtracts the number of dimensions in different behaviours. After varimax rotation, the component matrix provides us with a more easily interpretable solution. As shown in Table 2.3, four components are automatically extracted from the analysis and explain 60.6% of the total variance, confirming the importance of reading, computer usage on schoolwork, gaming, and school computer usage. These factors have higher scores following a variance analysis. The data-oriented nature of PCA makes it difficult to interpret each weight, which is often the case when the aim is to disentangle unobserved inter-relationships between various behaviours of young respondents. In general, the factor loadings doe not generate extreme weights of original behavioural variables, and some poorly-defined factors have been eliminated in our sample. The relatively average weights of different behaviours help identify some permanent elements of behavioural patterns and balance out the measurement errors and partial measures at different ages. I recognise that these PCA-constructed variables are "average proxies" for different behavioural patterns between age 14 and 15, and that real behaviours may vary according to data availability.

2.5.3.2 Effects on University Participation: With Controls for Behaviours

In this section, I present the results of treatment effects when behavioural variables are taken into account as an attempt to investigate underlying mechanisms. Through all specifications in Table 2.4, the treatment effect of having one's own computer is persistently positive and statistically significant at the 10% level. Due to data availability of behavioural variables, the working sample is further reduced to 6656. Both the ATT and ATE are reduced to 0.026, 0.024 respectively, a reduction of around 23% compared to the benchmark specification (7). The excluded 420 observations with more or less insufficient behavioural information might differ from the main sample: the proportion of university students among these young respondents is only 0.197, lower than the average of 0.328. Additional logistic regression shows that the average marginal effect reaches up to 0.118 among this group of students, which implies an increase by nearly 35% in their university attendance rate. Therefore, the average treatment effect might be larger than our estimates when policies are more concerned with disadvantaged students or families.

Specification (10) is therefore separately used as the baseline in this section for the purpose of comparison. In (11), the control for reading behaviour does not reduce the treatment effect or reduce the precision. An additional test shows an insignificant impact of having a personal computer on the change in reading habits defined as reading less often at age 17 than 15. Although I have no information about the exact timing of the ICT purchase between age 15 and 17, the results could be considered as support for a stable reading habit. Moreover, reading is a strong predictor of university attendance with an average marginal impact of 0.0567, conditional on all other covariates. If reading behaviour is less affected by computer usage but reflects one's particular pattern in information retrieving, our result suggests little impact of reading on the ICT effectiveness.

Including school ICT use does not affect the ATE estimates substantively. If students use a home computer more as a substitute for school ICT facilities, then we would expect decreased estimates. The measure of school ICT consists of two variables of usage in classes including ICT classes that deliver specific ICT knowledge to students. The chances are that students who use ICT more frequently at school might have better knowledge and awareness of ICT. Consequently, students could use ICT more efficiently at home in parallel with more ICT exposure at school, which would transfer into better academic outcomes. In practice, this impact might be small because a general control for school quality has already been incorporated.

On the subject of direct home ICT usage, playing computer games seems to not affect the treatment effects, albeit it is commonly considered as a typical distraction. When constructive computer use on schoolwork is incorporated, the ATT is reduced by 16% to 0.0216; the ATE is reduced to 0.0203. This constructive usage explains around 16% of treatment effects. The results in last two columns suggest that "doing homework" has a larger impact than "playing computer games" on the educational outcome, even it consists of many basic operations such as word processing and information searching.

In specification (14) when all four PCA-constructed behavioural variables are included, more variation appears in the propensity score distribution (Figure 2.2), ranging from 0.030 to 0.080 with ten blocks and a higher standard deviation of 0.075. All specifications are balanced regarding full covariates in the benchmark (7). The common support requirement does not lead to a reduction of observations more than 15. Additionally, it should be noted that the behavioural variables are measured before receiving a personal computer and are assumed to reflect students' general patterns in computer usage. It might be argued that students endogenously adjust themselves to a personal computer. Nonetheless, it is not our main research concern about ICT effectiveness in their next stage beyond high school, and it is less likely to see a significant transformation of these behaviours between age 17 and 19 according to current literature. Therefore, our matching estimates hold and demonstrate a consistently positive treatment effect of ICT investment on university participation.

2.5.4 Effects of ICT investment on University Type and Subject Choice

It would also be worth investigating whether the positive impact of personal computer holds for decisions over different university types. In our sample, I find that having own computer has zero impact on the likelihood of attending high-prestige Russell Group as shown in Table 2.5. In fact, reading behaviours and school performance are strongly positively associated with the possibility of attending Russell Group university, conditional on controls for family background. In our sample, around 16% of Russell-group students reported to have a laptop at age 14, 5% higher than other students. The difference in the new purchase of a laptop later, however, is statistically insignificant, and the proportion of laptop owners are similar at age 17. Our PSM estimates do not reveal a significantly positive impact on attending Russell Group universities.

Computers and ICT skills are also widely discussed in a context of a geek culture which might shape one's preference for subject choice. A recent study by Anesa Hosein (2019)(68) finds a positive association between playing computer games and pursuing a degree of Science, Technology, Engineering and Mathematics (STEM). Our data shows a significantly positive association but only conditional on HE participants. Again, the proportion of laptop owners are close across these two groups, as shown in the lower panel of Table 2.5. PSM estimates do not show a strong evidence of the impact on subject choice. The estimates are also statistically insignificant when the sample is further restricted to the HE participants. The inter-correlations between subject choice might be more attributable to innate interest. A laptop or desktop are more generally used in many aspects instead of some specialized STEM areas.

2.5.5 Heterogeneity

2.5.5.1 Gender

There has been increasing interest in gender difference in terms of attitudes towards technology or computers (Ardies *et al.*,2015(7); Potvin and Hasni,2014 *etc*(99).). Relative to boys, girls might have more negative attitudes and may be less actively engaged in technology-related activities. This study also demonstrates gender differences in a way. Boys are more likely to have their own computer as their average propensity score is approximately 13% higher than that of girls. Gender differences also exist in selected behaviours: reading, school and home ICT usage. On balance, boys tend to be more enthusiastic about computer-related activities than girls, as can be seen in the upper panel of Table 2.6.

The lower panel of Table 2.6 shows greater discrepancy insofar as the treatment effects of boys is almost twice as much as that of girls - this might be explained by some gender-specific behaviours. After controlling for these behaviours, the gender gap in treatment effects is narrowed. Boys are relatively more influenced by personal computers which increase their university participation by around seven percentage points on average; the same estimate is four percentage points for girls. However, such differences in the effect of a personal computer on university attendance are not statistically significant, partially owing to larger standard errors in subgroup analysis with fewer observations.

When computer-related behaviours are broken down further, it is observed that boys do not devote more time to schoolwork using a computer at home, and they play computer games much more than girls. Whereas girls, on average, have better reading habits and doing schoolwork. However, such constructive computer usage on schoolwork might be offset by their greater interest in online-chatting and music, or browsing probably. The results of this study are consistent with some literature showing no evidence of greater treatment effects of ICT for girls (Malamud *et al.,*2012(84); Faber *et al.,*2015(44)).

The gender gap is also often discussed when it comes to education attainment and participation. Some explanations include gender socialization and innate different interests and skills (Schoon and Ecceles 2014)(106)). But empirical evidence based on similar UK cohorts suggests that the gender gap in HE participation could be substantially reduced by including the prior academic attainment into account (Crawford and Greaves,2015(26)). We may conjecture that girls' decisions over higher education are not additionally affected by these ICTs but basically correspond to their academic performance in secondary school. For boys, the positive effect is still sensitive to the inclusion of behavioural variables that also relate to learning habits. A laptop might not necessarily switch some of their entertainment habits to more learning-oriented ones. Instead, it might promote their aspiration for the university where ICT can be more widely and freely used.

2.5.5.2 Family Background

It is of interest to investigate potential heterogeneity in the ICT effectiveness by family background. Parents play important roles in home ICT investment and may have additional influence on computer usage as a result of their different educational levels or working experience. As shown in Table 2.7, there appears to be a larger impact of personal computers on university participation for students with less educated parents, which is similar to the findings by Fiorni (2010)(52). Regarding family social-economic class, the ATT is around five percentage points and statistically significant for the groups of parents who hold intermediate occupations in sales, clerical, service and auxiliary. In the absence of significant difference in the propensity score of having own computer, our results suggest fewer impacts from the advantaged background but moderate positive impacts from other groups. The likely explanation is that the individual-specific computer purchase is more affected by students' every-day usage and preference instead of parental discipline.

2.5.5.3 Propensity Score Stratification

In general, the propensity score in our sample ranges from 0.3 to 0.8 and is mostly clustered around 0.5. It is worth recalling that observations within each stratum might have specific characteristics that are ambiguously reflected by the average treatment effects. Table 2.8 presents different matching results within different stratum that is divided to ensure the mean of covariates does not differ within each stratum. In the main specification, it seems that the estimated treatment effect is largely driven by the groups of people with higher propensity score over 0.6. The ATT reaches up to 0.045 in the group with relatively highest propensity score, compared to the average treatment effect 0.030 in the baseline specification. Figure 2.5 graphically plots the varying treatment effect using local polynomial regression [13](Fan and Gijbels 1996 (50)). We can observe the monotonically increasing treatment effect in the main specification but not for the other specification with behavioural variables. For the high-tendency group above 0.6, the treatment effect becomes smaller and statistically insignificant. These results show suggestive evidence of an inverted-U shape of the treatment effect that is usually higher between the 50 and 75 percentile than the other two extremes, which further highlights the importance of behavioural controls. It seems that personal ICT investment does not enhance the university attendance for the most computer desirers who might need them more out of entertainment purpose than e-learning. Apart from this discrepant trend, the estimates for the average population with propensity score between 0.5 and 0.6 are similar and consistently positive.

2.6 Robustness Checks

Having found a positive impact of having one's own personal computer on university participation, I next conduct several checks to verify our findings. As discussed earlier, the matching method cannot solve the selection problem caused by unobserved confounders. I therefore adopt the following methods to examine the unconfoundedness assumption by showing how the estimates change in response to potential confounders. Another concern is the implementation issue of choosing the most appropriate PSM estimator given our dataset. I checked the sensitivity of the results to different matching methods and select our preferred algorithm for its best performance in bias reduction.

2.6.1 Hidden Bias

2.6.1.1 Mantel-Haenszel (MH) Bounds

Firstly, Rosenbaum bounds (2002)(103) are used as the most common sensitivity test for matching, which provides evidence of the degree to which our results hinge on the CIA. The Mantel-Haenszel test compares the successful number of individuals in the treatment group against the same expected number given the treatment number is zero. This statistic can be bounded by two known distributions, which implies the bounds for over- and under-estimation. As a confounder changes value (in percentage), the treatment effect may become statistically insignificant. The degree of departure from a case that is free of hidden bias is measure by Γ. It is computed by e^{γ} where γ is the effect of a confounder on the participation decision(Becker and Caliendo, 2007(13))[14].

The highest Γ is 1.2 across all different specifications: the estimated ATT would be insignificant if an omitted characteristic make the odds ratio of having a personal computer for two respondents with the same observables differ by more than a factor of 1.2. In our sample, there are rarely extreme differences in odds ratios. For the dummy variable indicating "very likely to apply university", the difference in the relevant odds ratio is no more than five percentage point change (3.352 for the treated, 3.507 for the untreated). The difference in odds ratio is only seven percentages of high family income. Taken together, I cannot state the absence of unobserved heterogeneity, but the balance of confounders in our sample supports the validity of our identification.

2.6.1.2 Simulation Method

Building on the Rosenbaum and Rubin (1983)(104) and Rosenbaum(1987)(102), the potential confounder can also be simulated in the data and used as an additional covariate in combination with the preferred matching estimator. The comparison between different results with or without this confounder shows how the baseline results can be affected by this potential source of deviation of CIA. Specifically, this simulation method computes the effects of a confounder on the relative probability to have a positive outcome in case of no treatment ("outcome effect") and the relative probability to be assigned to the treatment ("selection effect").

The simulated treatment effects are consistently 0.030 with a standard deviation of 0.012, which shows no difference at a three digit level compared to its own simulation benchmark that is exactly 0.030[15] as well. The simulated covariates include some variables in our main specification and other potential factors recorded in the dataset. As shown in Table 2.9, the confounder "very likely to apply for university" has the greatest outcome effect of increasing the probability of attending university by a factor of 3.5. However, it does not substantially affect participation decision, which might conflict with the common perception that personal computers are essential preparation for a campus life. The ICT relevant covariates ("like ICT" "good at ICT") have positive selection effect, which accords with common perception. Being well capable of using ICT can increase the relative probability of having own computer by a factor of 1.5. As for other family factors, the indicator for high-income family (defined by the variable of income bandwidths above 41,000 pounds) is positively associated with both outcome and treatment status but does not affect ATT much. Students with extra siblings are less likely to receive individual computer but have similar university attendance rates.

Apart from the observed covariates in our dataset, Table 2.10 presents how results might change in response to other unknown variables of which probability parameters can be arbitrarily specified. The first column gives the baseline simulation when the treated and control groups are free from the impact of any confounder, as reflected by the same parameters used for calculating outcome or selection effect in this algorithm. These parameters are randomly chosen to characterise different possibilities of having a confounder in relevant groups. Even the confounder in (6) with a high selection effect does not pose a threat to the baseline estimate. In this case, even the difference in the probability of having the confounder is over six times higher in the participants than the untreated, the treatment effect is maintained at 0.030. In sum, above simulation yields consistent outcomes, suggesting the robustness of our estimates.

2.6.2 Matching Algorithms

The PSM estimators differ not only in the way the neighbour is defined or searched but the weights given to comparable controls. All PSM estimators should give similar results as the sample size increases (Smith 2000(114)) because it is more likely that there are sufficient untreated individuals for matching. In small samples, algorithm selection is important as there exist different trade-offs between bias and efficiency (Heckman *et al.*,1997(64)). In practice, the choice is largely dependent on the real situation and data structure at hand. If there are many control observations, it is better to use more than one exact matching method to increase precision.

Table 2.11 presents results from PSM using different algorithms. In the most straightforward nearest neighbour matching, individuals from the control group are chosen as a matching partner for a treated person that is closest in terms of propensity score. It is noticed that the nearest neighbour matching without replacement increases sample bias of two percentages as we lose information about over 900 treated individuals over the range of common support. The ATT is smaller than all other estimates by almost a third. However, we can improve matching quality by allowing multiple comparable observations and replacement.

By imposing a tolerance level of maximum propensity score distance, radius matching (Dehejia and Wahba 2002(33)) enables matching all comparisons within a more precise calliper. We can expect fewer bad matches and improved quality, but we cannot foresee or determine the most effective calliper (Smith and Todd 2005(114)). In our main specification (7), the starting calliper is set to be 0.25 of the standard deviation of the estimated propensity scores. A smaller calliper ensures that the matched neighbour is not far away from the treated and is replaceable when a better one within the calliper appears, which shares the same advantage in oversampling method and increases matching quality. The treatment effects are less sensitive to changes of radius calliper especially in a direction for closer matching. The balance tests also support this method as our preferred one because of highest bias reduction between the treatment and control groups.

In kernel matching, all individuals in the control group are used to construct a weighted average. The weights depend on the distance between each from the control group and the treated; higher weights are put on closer observations in terms of the propensity score. The kernel function is suggested to be unimportant in practice (DiNardo and Tobias 2001(34)), but the choice of bandwidth parameter implies the trade-off between a better fit and higher variance. This can be reflected in the third panel of Table 2.11: ATT is increasingly precise as the smaller bandwidth keeps more underlying features in the sample. Kernel matching with a bandwidth 0.01 yields a better result that is similar to our preferred matching.

On the whole, different matching methods yield consistently positive treatment effect at the one percent level and similar estimates around 0.030.

2.7 Conclusion

Increases in ICT investment may not necessarily produce the anticipated improvement in learning outcomes. The current literature shows mixed results about the impact of school ICT investment for educational purposes. The net effects of ICT investment are ambiguous in the presence of competing impacts. On the one hand, students could access more tailored learning and online resources. On the other hand, more distractions arise from other usages such as online shopping and computer games. With increasing digitalisation in learning resources, it is worth investigating ICT in a home context on account of higher accessibility, flexibility, and autonomy.

This paper presents Propensity Score Matching (PSM) results that adjust for selection bias in estimating treatment effect in a non-experimental setting. Estimates from the Longitudinal Study of Young People in England (LSYPE) demonstrate the positive impact of ICT investment in a home setting, which is consistent with other research based on a large population sample. Also, this large survey data permits us to achieve good matches and precise estimates. I find that young students who received their own computer between age 15 and 17 are three percentage points higher in the probability of attending university later. The results are robust to different tests on possible confounders that may impede valid identification. To further explain the positive impact, I investigate the underlying mechanism by incorporating relevant behaviours into the main regression as controls for potential behavioural patterns that are often tested and suggested less responsive to ICT treatment in existing literature. There is no strong evidence of the negative impact of playing computer games. Whereas, computer usage on schoolwork is influential as it may reflect underlying learning attitudes. Ultimately, the positive impact of having a personal computer at home on university participation remains positive and statistically significant when relevant behaviours are accounted for. There is also no clear evidence on whether this impact is related to institution types or subjects choice.

I also draw attention to the heterogeneity of the treatment effect. First, the estimated treatment effects are much higher for boys than girls even when boys devote more time to computer games on average. But this gender gap is narrowed when behavioural controls are introduced, which implies the importance of computer-specific usage in explaining ICT effectiveness. Second, parental factors appear to less affect the impact of the personal computer on university participation. The treatment effect is not particularly strong in the case of advantaged family background. There is also some suggestive evidence of an inverted-U shape of the treatment effect as the estimated treatment effects are primarily driven by the groups of observations with an average tendency to buy a personal computer rather than very few extreme ICT enthusiasts.

Limitations of this study include the reliance on self-reports for students' academic performance and school quality. Using more detailed test scores, I could better test and control for the endogenous purchase of personal computers. Besides, the estimation may be sensitive to the linear specification of propensity score in our estimation that lacks continuous covariates. As for behavioural variables, data availability largely determines the identifiable dimensions of behavioural patterns in the principal component analysis. It would have been better to include more information in their following years after age 15 and other activities such as watching TV and doing sports, which might better capture potential substitution in their time allocation.

Consistent with existing literature, I do not find a sizeable impact of having a personal computer or laptop on educational outcomes. Our results suggest potential benefits of higher university participation. As the purchase cost of computers declines, home ICT investment merits consideration and is not merely a material preparation for university. Moreover, it may be not necessarily detrimental in a context of increasing digital exposure as long as the young develop a better awareness of relevant merits and effective usage. In essence, technical advancement is capable of providing students with a better platform for retrieving plenty of resources, but not making more sense of knowledge. In this context, further attention could extend to the second level of the digital divide from the human capital perspective. Future research could focus on underlying interaction between various skills and ICT investment, especially the noncognitive aspect that plays an important role in self-directed learning.

2.8 Tables and Graphs

Table 2.1: Descriptive Statistics

	N	Mean	S.D.	Treated	Control	Diff(t-test)
Having Own Laptop/computer (age 17)	9448	0.567	0.495			
Having Own Laptop/computer (age 15)	8618	0.115	0.319			
Studying for a University Degree (age 19)	9538	0.328	0.469	0.364	0.327	0.036***
Male	9538	0.493	0.499	0.522	0.456	0.066***
White	9538	0.677	0.467	0.695	0.685	0.011
Black	9538	0.111	0.314	0.119	0.094	0.025***
Cohort born in 1990	9538	0.672	0.469	0.677	0.681	-0.005
School Quality - Fairly Good (age 14)	9538	0.453	0.498	0.447	0.433	0.014
School Quality - Fairly Bad (age 14)	9538	0.030	0.171	0.024	0.023	0.001
School Performance - Very Good (age 14)	9538	0.200	0.400	0.224	0.199	0.025***
School Performance - Below Average (age 14)	9538	0.032	0.177	0.019	0.027	-0.008***
Ever Smoke (age 14)	9538	0.030	0.298	0.063	0.083	-0.020***
Highest qualification held by main parent						
Higher education qualification	9538	0.134	0.341	0.127	0.132	0.005
GCE A level	9538	0.144	0.351	0.131	0.152	-0.021*
GCSE grades A-C	9538	0.273	0.446	0.271	0.270	0.001
No qualification	9538	0.221	0.414	0.204	0.191	-0.013
Family SEC						
Higher Managerial and professional occupations	9538	0.125	0.331	0.130	0.129	0.000
Lower managerial and professional occupations	9538	0.230	0.421	0.238	0.244	0.006
Small employers and own account workers	9538	0.115	0.319	0.122	0.111	0.011
Routine	9538	0.103	0.305	0.093	0.103	0.010*
Never worked/long term unemployed	9538	0.052	0.223	0.050	0.045	0.005
Home pc access	9538	0.879	0.326	0.950	0.947	0.003
Household Annual Salary	6927	31166.26	31250.83	34178.20	32763.90	1414.20*
Parents Involvement -Very Involved	9538	0.243	0.429	0.233	0.227	0.006
Parents Involvement -Not very Involved	9538	0.238	0.043	0.248	0.251	-0.003

Note: *** significant at 1% level; ** at 5% * at 10%.

Table 2.2: Effect of ICT investment on University Participation by Logit and PSM

Y: studying for a university degree									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Method	Logit	Logit	Logit	Logit	Logit	Logit	PSM (logit)	PSM (logit)	PSM (probit)
D: Own laptop/pc									
ATT							0.0321***	0.0321***	0.0319***
							(0.012)	(0.012)	(0.012)
ATE							0.0300***	0.0302***	0.0300***
							(0.012)	(0.012)	(0.012)
Odds Ratio	1.174***	1.208***	1.212***	1.179***	1.182***	1.159***			
	(0.057)	(0.060)	(0.062)	(0.062)	(0.063)	(0.062)			
Average Marginal Effect	0.036***	0.042***	0.040***	0.034***	0.035***	0.029***			
	(0.011)	(0.011)	(0.010)	(0.011)	0.0110	(0.011)			
Controls									
Gender, ethnicity, cohort		√	√	√	√	√	√	√	√
Family backgrounds			√	√	√	√	√	√	√
Whether smokes				√	√	√	√	√	√
School's quality					√	√	√	√	√
Performance at school						√	√	√	√
Pseudo R^2	0.001	0.013	0.062	0.071	0.073	0.091			
N	7568	7568	7460	7105	7105	7076	7072	7076	7071

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% In matching specifications (7)-(9), 4, 0, 5 observations were dropped respectively due to common support restriction. (7) is the preferred specification. The estimated ATT/ATE are calculated to four decimal places to show more detailed differences. The propensity score is estimated using a logit of treatment status on all covariates linearly. The controls for family backgrounds include parents' educational qualification, social economic class, standardised household annual income, household computer access and parents' involvement in children's school life.

Table 2.3: Construction of Behavioural Variables by PCA

Variable	Component 1	Component 2	Component 3	Component 4
Reading for pleasure (age 14)	**0.5644**	0.0533	0.0122	0.0093
Reading for pleasure (age 15)	**0.6066**	-0.0165	0.0131	-0.0007
Reading for pleasure (age 17)	**0.5575**	-0.0340	-0.0220	-0.0064
Use pc at home for schoolwork (age 14)	-0.0177	**0.7011**	0.0024	0.0194
Use pc at home for schoolwork (age 15)	0.0174	**0.7035**	-0.0052	-0.0241
Use pc at home for game (age 14)	0.0052	0.0071	**0.7044**	0.0221
Use pc at home for game(age 15)	-0.0014	-0.0101	**0.6999**	-0.0215
Use pc on ICT class at school (age 14)	-0.0074	-0.0678	0.0184	**0.5905**
Use pc on ICT class at school (age 15)	-0.0242	0.0667	0.0731	**0.5540**
Use pc on non-ICT classes at school (age 15)	0.0332	0.0080	-0.0860	**0.5851**

Note: Four components are identified as: reading for pleasure; doing schoolwork using home pc; playing games using home pc; use pc at school. The rotation is based on the variance max criterion. The table shows the respective factor loadings of the behavioural variables measured at different time.

Table 2.4: Effect of ICT investment on University Participation with Behavioural Controls: PSM Estimation

Y: studying for a university degree	(10)	(11)	(12)	(13)	(14)
D: own laptop/pc					
ATT	0.0258**	0.0256**	0.0261**	0.0259**	0.0216*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ATE	0.0241**	0.0241**	0.0244**	0.0252**	0.0203*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Behavioural Controls					
Reading		√	√	√	√
Using pc at school			√	√	√
Playing pc games				√	√
Doing schoolwork on pc at home					√
Other Controls	√	√	√	√	√
N	6652	6652	6652	6651	6641

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% The restricted sample with full behaviour information is 6656, compared to 7076 in the baseline. In specification (10)-(14), 4, 4, 4, 5, 15 observations were dropped respectively due to common support. The estimated ATT/ATE are calculated to four decimal places to show more detailed differences. Behavioural variables are constructed and standardised by principal component analysis with a mean of 0 and standard deviation of 1. Controls include: gender, ethnicity, cohort , whether smokes, school's quality(fairly good), school performance(very good), highest qualification held by main parent, social economic class, standardised annual salary, parents' involvement in students' school life (very involved), home computer access. The propensity score was estimated using a logit of treatment status on all covariates linearly.These covariates were all balanced in all specifications.

Table 2.5: Effect of ICT investment on University Type and Subjects

Panel A: University Type	**Russell Group**		**Other Institutions**	
ATT	-0.008	-0.004	0.0361***	0.0276*
	(0.009)	(0.009)	(0.014)	(0.015)
Mean(Y=1)	0.087	0.089	0.291	0.298
	(0.281)	(0.285)	(0.454)	(0.458)
Mean(D=1)	0.567	0.569	0.567	0.567
	(0.495)	(0.495)	(0.496)	(0.495)
Behavioural Controls		√		√
Treated (off-support)	3062(4)	3764(15)	3062(4)	3764(15)
Controls(off-support)	4010(0)	2873(4)	4010(0)	2873(4)
N	7076	6656	7076	6656
Panel B: Subjects Choice	**STEM**		**Non-STEM**	
ATT	0.018**	0.010	0.013	0.009
	(0.009)	(0.009)	(0.010)	(0.011)
Mean(Y=1)	0.157	0.161	0.221	0.227
	(0.363)	(0.367)	(0.415)	(0.419)
Mean(D=1)	0.567	0.568	0.567	0.568
	(0.495)	(0.495)	(0.496)	(0.495)
Behavioural Controls		√		√
Treated (off-support)	3062(4)	3764(15)	3062(4)	3764(15)
Controls(off-support)	4010(0)	2873(4)	4010(0)	2873(4)
N	7076	6656	7076	6656

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10%.

Table 2.6: Heterogeneity in the Effect of ICT investment by Gender

Panel A: Descriptions of ICT behaviours and attitudes	**Boys**		**Girls**	**t-diff**
Read (most days)	0.328		0.448	-0.122
Computer-related Activities				
Schoolwork ($\geqslant$ 3 days)	0.234		0.268	-0.034***
Game (most days)	0.343		0.137	0.205***
Word processing, spreadsheet	0.315		0.312	0.005
Emails	0.480		0.621	-0.134***
Chatrooms	0.310		0.356	-0.046***
Listening to Music	0.638		0.681	-0.048***
PC use at school ($\geqslant$ 3 days)	0.268		0.270	-0.072***
Attitudes to ICT				
Very Like ICT	0.571		0.372	0.198***
Very Good at ICT	0.360		0.237	0.125***
Very important in study	0.382		0.334	0.048***

Panel B: PSM estimates	**Boys**		**Girls**	
	(1)	(2)	(3)	(4)
ATT	0.0427***	0.0221	0.0193	0.0170
	(0.016)	(0.017)	(0.016)	(0.017)
Mean (Y=1)	0.324	0.334	0.385	0.394
Mean (D=1)	0.600	0.602	0.532	0.531
Mean Propensity Score	0.600	0.600	0.533	0.533
	(0.040)	(0.040)	(0.044)	(0.044)
Behavioural Controls		√		√
Treated (off-support)	2125 (1)	1983 (16)	1882 (2)	1774 (6)
Controls (off-support)	1411 (3)	1311 (0)	1649 (3)	1561 (5)
N	3540	3310	3536	3346

Note: Robust standard errors are in parentheses. Standard deviations in parentheses for mean propensity score. *** significant at 1% level; ** at 5% * at 10% . Panel A shows the means of ICT-related variables (at age 14) among boys and girls. For the estimation within each gender group, specifications are same as the baseline regression.

Table 2.7: Heterogeneity in the Effect of ICT investment by Family Backgrounds

Panel A: Subgroups by Parent's NVQ	**University Higher/First Degree**		**A/AS level or equiv**		**GSCE grades or equiv**		**No qualification**	
ATT	0.0284	0.0157	0.0365	0.0392	0.0312*	0.0172	0.0370	0.0223
	(0.034)	(0.035)	(0.031)	(0.032)	(0.018)	(0.019)	(0.025)	(0.027)
Mean (Y=1)	0.534	0.538	0.361	0.367	0.290	0.300	0.297	0.314
Mean (D=1)	0.558	0.558	0.538	0.540	0.564	0.564	0.582	0.586
Mean propensity score	0.558	0.559	0.537	0.540	0.564	0.564	0.582	0.586
	(0.050)	(0.074)	(0.049)	(0.071)	(0.051)	(0.073)	(0.056)	(0.072)
Behavioural Controls		√		√		√		√
Treated (off-support)	520 (0)	499 (1)	531 (9)	510 (10)	1396 (1)	1294 (10)	810 (2)	737 (4)
Controls (off-support)	409 (2)	392 (3)	464 (0)	441 (1)	1075 (3)	1009 (0)	578 (3)	519 (4)
N	931	895	1004	962	2475	2313	1391	1264
Panel B: Subgroups by Parent's SEC	**Managerial/Professional**		**Intermediate**		**Semi-routine/Routine**		**Never worked/Unemployed**	
ATT	0.0131	0.0036	0.0525**	0.0473*	0.0183	-0.0003	0.0638	0.1030**
	(0.019)	(0.020)	(0.026)	(0.028)	(0.019)	(0.020)	(0.052)	(0.056)
Mean (Y=1)	0.457	0.460	0.345	0.357	0.251	0.263	0.276	0.302
Mean (D=1)	0.560	0.557	0.595	0.598	0.550	0.553	0.595	0.591
Mean propensity score	0.560	0.558	0.595	0.598	0.550	0.553	0.595	0.591
	(0.049)	(0.073)	(0.052)	(0.073)	(0.052)	(0.072)	(0.056)	(0.075)
Behavioural Controls		√		√		√		√
Treated (off-support)	1498 (3)	1425 (7)	777 (1)	735 (5)	1188 (1)	1095 (6)	190 (4)	162 (6)
Controls (off-support)	1175 (3)	1131 (4)	527 (2)	495 (1)	969 (1)	888 (1)	130 (2)	114 (2)
N	2679	2567	1307	1236	2158	1990	326	284

Note: Robust standard errors are in parentheses. Standard deviations are in parentheses for mean propensity score. *** significant at 1% level; ** at 5% * at 10% . The upper panel shows matching results within different groups of parental highest qualification. The lower panel shows matching results within different family social economic class that is based on National Statistic's Socio-economic Classification(NS-SEC). "Managerial/professional" includes both high and low professional/managerial occupations, high supervisory and high technical occupations and employers in large organisations. "Intermediate" includes employers in small organizations, own account workers and intermediate positions that do not involve general planning or supervisory powers. "Semi-routine/routine" includes occupations in sales, service, agricultural, clerical etc, which conventionally is known as "semi-skilled" and "unskilled" occupations.

Table 2.8: Heterogeneity in the Effect of ICT investment by Propensity Score Stratum

Panel A: Baseline Estimates				
Propensity Score Stratum:	(0.4, 0.5)	(0.5, 0.6)	(0.6, 0.7)	
ATT	-0.0010	0.0281*	0.0452**	
	(0.032)	(0.014)	(0.022)	
Mean(Y=1)	0.301	0.337	0.348	
Mean(D=1)	0.454	0.556	0.635	
Mean propensity score	0.473	0.554	0.629	
	(0.021)	(0.027)	(0.024)	
Treated (off-support)	363 (7)	2340 (1)	1295 (3)	
Controls (off-support)	443 (1)	1868 (0)	746 (1)	
N	814	4209	2045	
Panel B: Estimates with Behavioural Controls				
Propensity Score Stratum:	(0.3, 0.5)	(0.5, 0.6)	(0.6, 0.7)	(0.7, 0.8)
ATT	-0.0100	0.0359**	0.0128	0.0500
	(0.028)	(0.017)	(0.021)	(0.074)
Mean(Y=1)	0.367	0.366	0.356	0.387
Mean(D=1)	0.449	0.558	0.637	0.714
Mean propensity score	0.459	0.551	0.640	0.726
	(0.032)	(0.028)	(0.026)	(0.022)
Treated (off-support)	562 (2)	1724 (0)	1318 (6)	147 (20)
Controls(off-support)	690 (2)	1359 (3)	754 (0)	67 (0)
N	1256	3086	2078	234

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10%. For each matching process, different stratum of propensity score is identified so that the mean of covariates does not differ within stratum. In panel A, the results are based on the baseline specification (7) in Table 2.2, with five strata. The common support range is (0.395, 0.713). The first stratum is dropped since there is no applicable matching among four observations. In panel B, the results are based on the specification (14) in Table 2.4 with behavioural controls, with 10 strata identified. The common support range is (0.325, 0.800). A few original strata have been merged for better matching result. Radius matching is applied to all within-stratum observables.

Table 2.9: Hidden Bias Check: Simulation of Observed Variables

Simulated Confounder	**ATT(simulated)**	**(s.e)**	**Outcome Effect**	**Selection Effect**
White	0.030	(0.012)	0.607	1.044
School performance (above average)	0.030	(0.012)	1.546	1.119
School quality (very good)	0.030	(0.012)	1.457	0.963
School quality (fairly bad)	0.030	(0.012)	0.497	1.071
Ever smoke	0.030	(0.012)	0.394	0.739
Read (most days)	0.030	(0.012)	1.885	0.980
Very likely to apply	0.030	(0.012)	3.561	1.156
Like ICT a lot	0.030	(0.012)	0.885	1.378
Good at ICT	0.030	(0.012)	1.190	1.524
Watching TV (>7 hours after school)	0.030	(0.012)	0.833	1.018
High annual income (>41000)	0.030	(0.012)	1.946	1.185
Has extra sibling	0.030	(0.012)	0.976	0.625

*Note:*Standard errors are in parentheses. All the simulated confounders are binary variables as required. The outcome effect is the effect of a confounder on the relative probability to have a positive outcome in case of no treatment. The selection effect is the effect of a confounder on the relative probability to be assigned to the treatment.

Table 2.10: Hidden Bias Check: Simulation of Unobserved Variables

	(1)	(2)	(3)	(4)	(5)	(6)
p_{11}	0.50	0.80	0.80	0.10	0.10	0.90
p_{10}	0.50	0.50	0.80	0.80	0.40	0.80
p_{01}	0.50	0.50	0.20	0.80	0.80	0.20
p_{00}	0.50	0.50	0.50	0.50	0.60	0.10
p_1	0.50	0.61	0.80	0.55	0.29	0.84
p_0	0.50	0.50	0.40	0.60	0.67	0.13
Outcome Effect	1.031	1.008	0.244	4.126	2.730	2.246
Selection Effect	1.002	1.573	6.131	0.786	0.200	34.545
ATT	0.030	0.030	0.030	0.030	0.030	0.030
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)

Note: p_{11} is the probability of having a confounder U =1 if D=1 and Y=1 ;
p_{10} is the probability of having a confounder U =1 if D=1 and Y=0;
p_{01} is the probability of having a confounder U =1 if D=0 and Y=1;
p_{00} is the probability of having a confounder U =1 if D=0 and Y=0;
p_1 is the probability of having a confounder U =1 if T=1;
p_0 is the probability of having a confounder U =1 if T=0
Common support condition has been imposed in all simulations with 100 iterations and logit estimation. Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10%.

Table 2.11: Sensitivity to Matching Algorithms

Method	**Treated** (off support)	**Controls** (off support)	**ATT**	**(s.e)**	**Bias Reduction** (%)
Nearest Neighbour					
nn (1) without replacement	3062 (948)	3062 (4)	0.0225**	(0.012)	-2.0
nn (1) with replacement	4010 (0)	3062 (4)	0.0356***	(0.016)	10.4
nn (3) with replacement	4010 (0)	3062 (4)	0.0330***	(0.013)	14.0
nn (10) with replacement	4010 (0)	3062 (4)	0.0303***	(0.012)	15.1
Radius					
Radius (r = 0.1)	4010 (0)	3062 (4)	0.0301***	(0.0116)	6.2
Radius(r = 0.01)	4010 (0)	3062 (4)	0.0321***	(0.0116)	20.7†
Radius (r = 0.005)	4009 (1)	3062 (4)	0.0319***	(0.0117)	19.3
Radius (r = 0.001)	3993 (17)	3056 (10)	0.0319***	(0.0119)	17.8
Kernel					
Normal (bandwidth = 0.1)	4010 (0)	3062 (4)	0.0300***	(0.0117)	3.8
Normal (bandwidth = 0.06)	4010 (0)	3062 (4)	0.0303***	(0.0117)	7.5
Normal(bandwidth = 0.01)	4010 (0)	3062 (4)	0.0321***	(0.0116)	19.2
Normal(bandwidth = 0.001)	4010 (0)	3062 (4)	0.0318***	(0.0118)	18.4
Biweight (bandwidth = 0.01)	4010 (0)	3062 (4)	0.0319***	(0.0116)	19.4

Note: *** significant at 1% level; ** at 5% * at 10%. The radius matching with a caliper 0.01 is chosen as the preferred. In the second and third columns, the numbers in brackets are the number of observations dropped due to matching restrictions. The bias reduction is absolute difference in covariates bias that is calculated in percentage before and after matching.

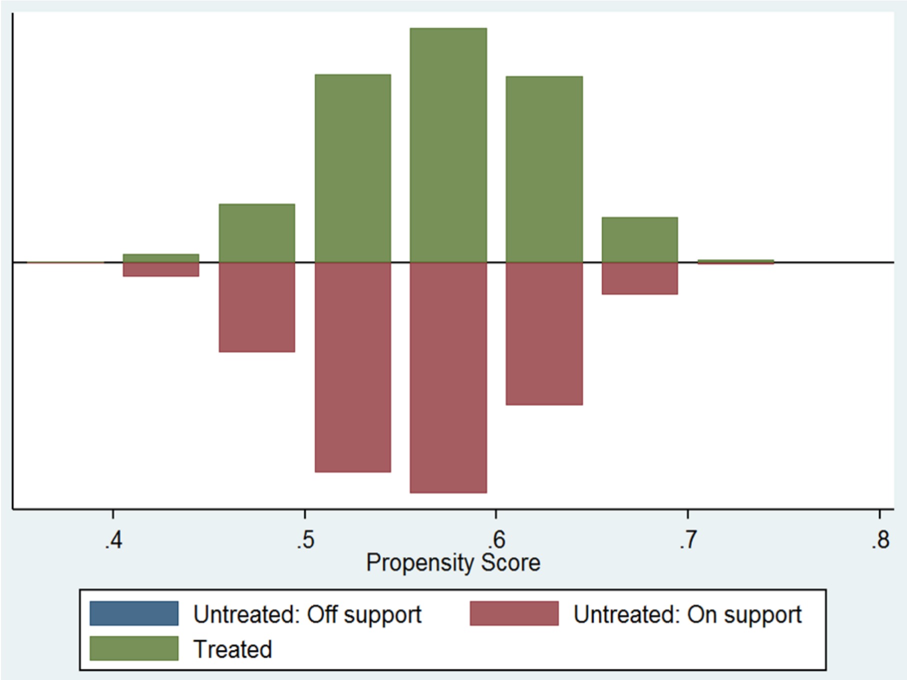


Figure 2.1: Propensity Score Distribution (baseline specification)

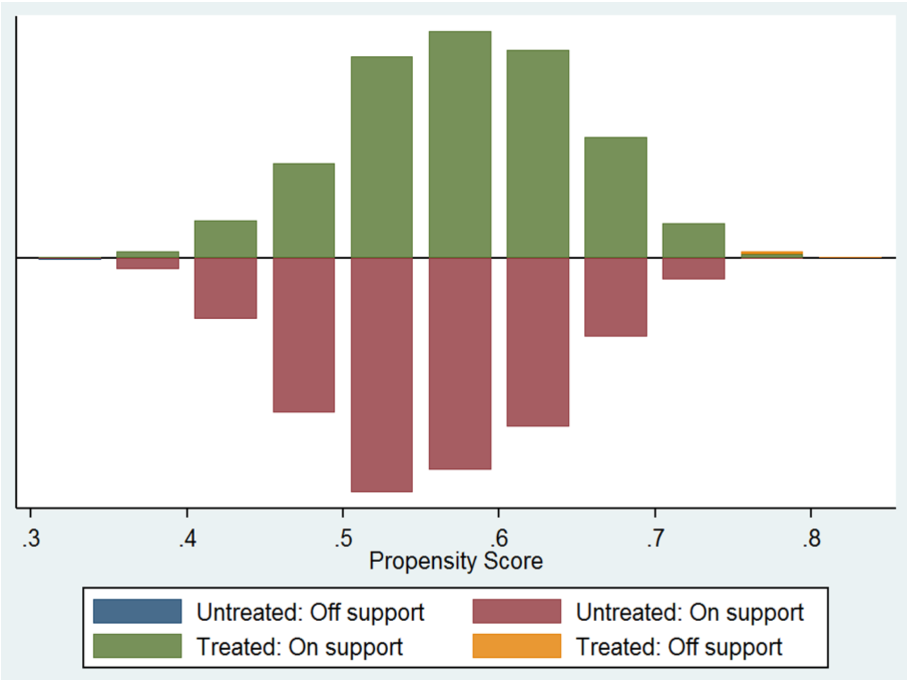


Figure 2.2: Propensity Score Distribution (specification with behavioural controls)

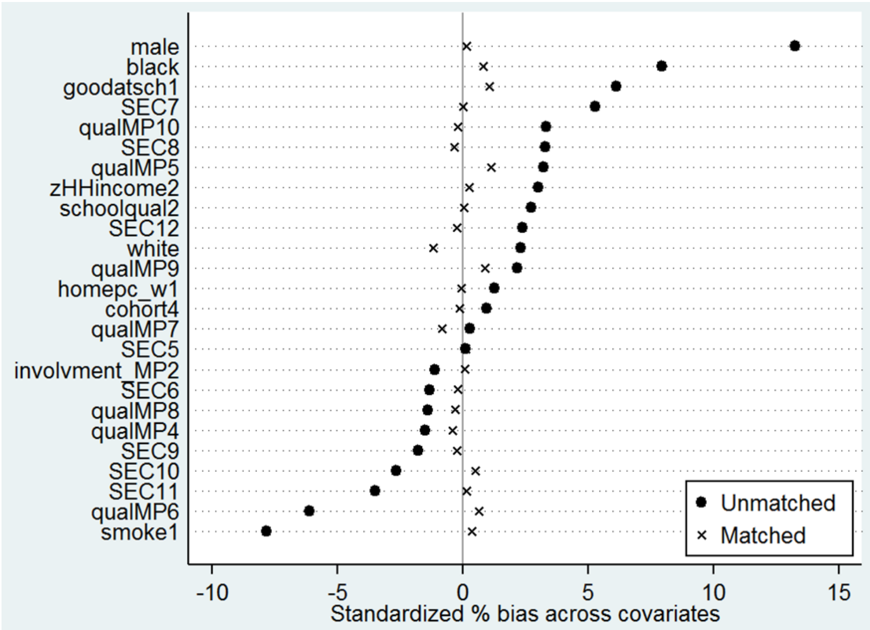


Figure 2.3: Balance Plot (baseline specification)

Note: Variables are described in Appendix Table 5.4.

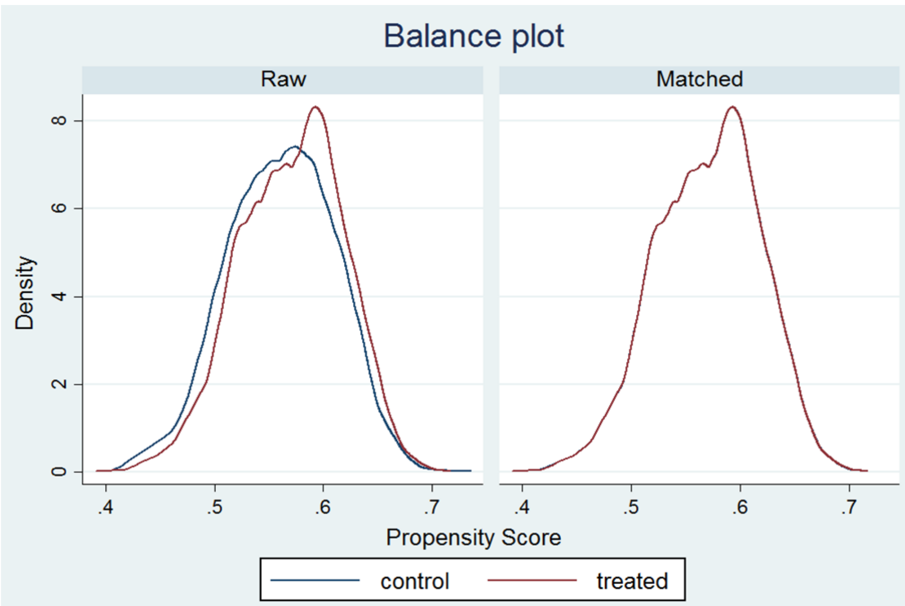


Figure 2.4: Density Plot (baseline specification)

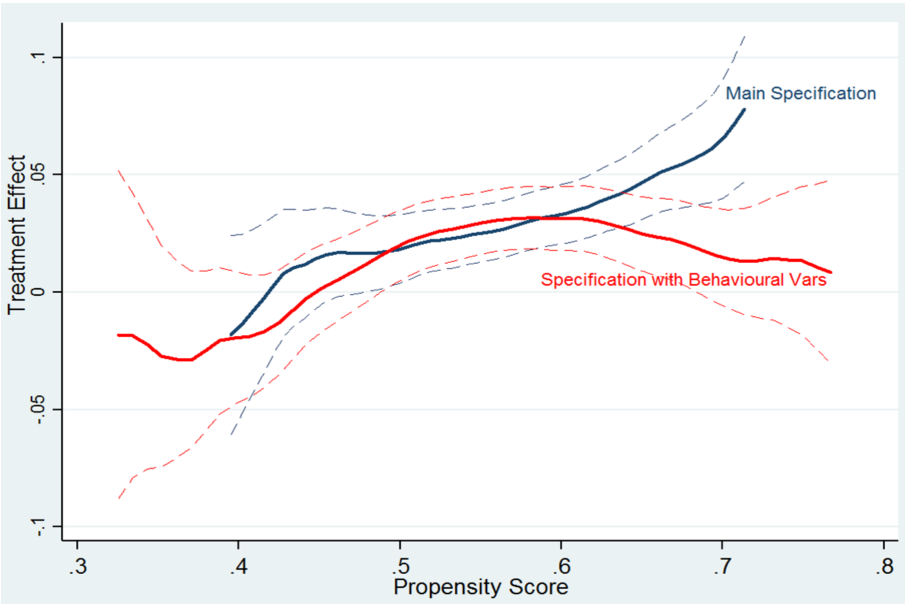


Figure 2.5: Heterogeneity in Treatment Effect by Propensity Score

2.9 Appendix

Table 2.12: Descriptive Statistics of Relevant Activities

	N	Treated	Control	Diff (t-test)
Reading for pleasure (age 14)				
Most days	9356	0.384	0.375	0.009
Once a week	9356	0.169	0.164	0.004
Hardly ever	9356	0.084	0.091	-0.006
Using home pc for schoolwork (age 14)				
Most days	7754	0.071	0.055	0.016**
3-4 days a week	7754	0.194	0.165	0.029***
less than one day	7754	0.197	0.223	-0.026**
Playing computer games (age 14)				
Most days	9416	0.266	0.207	0.059***
3-4 days a week	9416	0.163	0.145	0.010
1-2 days a week	9416	0.350	0.380	-0.030**
PC use in ICT classes at school (age 14)				
Most days	9117	0.025	0.025	0.000
3-4 days a week	9117	0.049	0.046	0.002
1-2 days a week	9117	0.754	0.725	0.029**
PC use in other classes at school (age 14)				
Most days	9094	0.121	0.099	0.022***
3-4 days a week	9094	0.340	0.352	-0.011
1-2 days a week	9094	0.428	0.434	-0.006

Note: *** significant at 1% level; ** at 5% * at 10%

Table 2.13: Variable Definition

Variable Name	Definition
Schoolwork-home	The frequency of using computer for schoolwork at home per week
Game-home	The frequency of playing computer games at home per week
Schoolusage	The frequency of ICT usage in school (on both computing or non-computing class)
Reading	The frequency of reading for pleasure per week
White	Ethnic group (Including white-British, Irish, and other white backgrounds)
Black	Ethnic group
homepc-w1	Household has a computer at home
zHHincome	Standardised Household annual salary
Smoke1	Whether ever smoked cigarettes
Cohort4	The cohort born in 1990
Schoolqual	Overall school quality (self-reported by young respondents)
goodatsch	Good at school work (self-reported by young respondents)
qualMP4	Highest Qualification (main parents): Degree
qualMP5	Highest Qualification (main parents): Higher education below degree level
qualMP6	GCE A level or equivalent
qualMP7	GCSE grades A-C or equivalent
qualMP8	Qualifications at level 1 and below
qualMP9	Other qualification
qualMP10	No qualification
SEC5	Higher managerial, administrative and professional occupations
SEC6	Lower managerial, administrative and professional occupations; higher technical or supervisory occupations
SEC7	Intermediate occupations (clerical, sales , service, technical and auxiliary)
SEC8	Small employers and own account workers
SEC9	Lower supervisory and technical occupations
SEC10	Semi-routine occupations (sales, service, technical, agricultural, clerical, childcare)
SEC11	Routine occupations (sales, service, production, operative, agricultural)
SEC12	Never worked/long term unemployed
Involvement (main parent)	The main parent' involvement in young respondent' school life

Note: The "main parent" is identified as the right parent/person who is most involved in young person's education. National Statistic's Socio-economic Classification(NS-SEC) is used as a control for family social economic class.

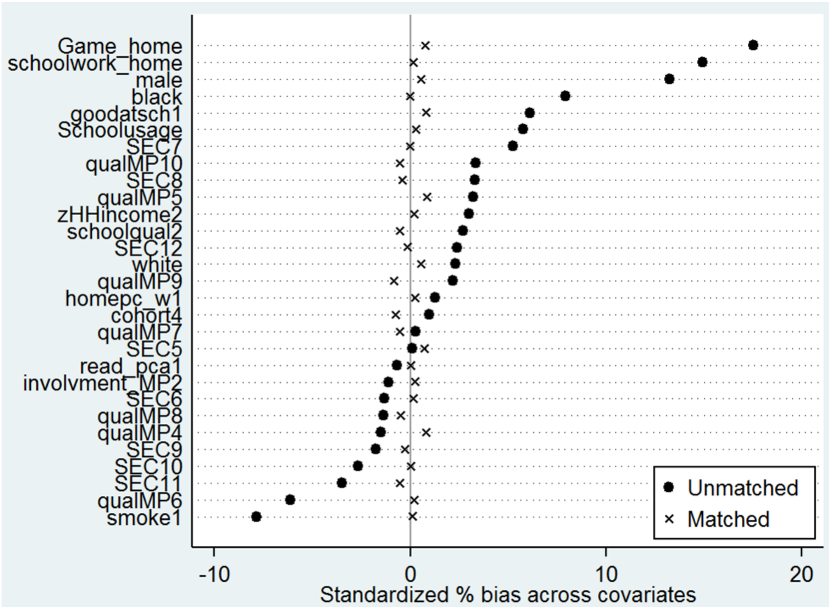


Figure 2.6: Balance Plot(specification with behavioural controls)

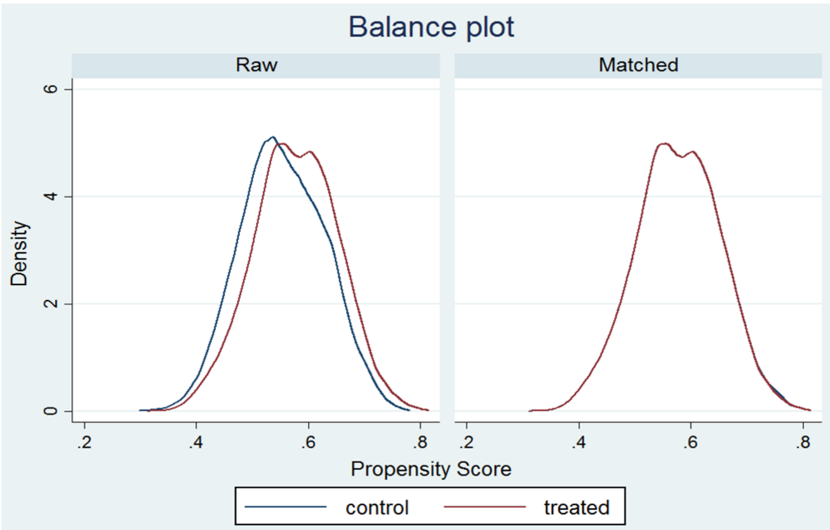


Figure 2.7: Density Plot (specification with behavioural controls)

Notes

[1]Based on Common Population Survey(1984-2012)

[2]Based on Longitudinal Study of Young People in England(2004-2010)

[3]The intervention of Pratham takes advantage of the governmental policy in Gujarat that delivered four computers to every 100 primary schools in Vadodara (80% of schools).

[4]In 1994, The Israeli State lottery provided new computers to many elementary and middle schools.

[5]Such as Fast ForWord(FFW), Supporting programs in Texas Technology Immersion Pilot(TIP).

[6]See the example of Texas Immersion Technology Pilot (Shapley *et al.*,(109)).Only 6 of 21 schools reached substantial levels of implementation by the end of fourth year.

[7]the Current Population Survey(CPS) and the National Longitudinal Survey of Youth 1997 (NLSY97)

[8]They estimated fixed effect models, bivariate probit and two-stage least squares(2SLS). The instruments used in their work is the parental use of the Internet at work and the presence of another teenager in household.

[9]The LEAs by districts further allocate funding to schools. Hence, the rule change is at LEA level.

[10]Currently named as Next Steps

[11]Fieldwork for the first four waves was carried out by BMRB social research, GfK NOP and Ipsos MORI. Wave five and six were carried out by BMRB and GfK only. Respondents could choose between online, telephone and face-to-face interview. In wave five, only young people were interviewed.

[12]The Higher Education Initial Participation Rate (HEIPR) for English domiciled young people ages 17-19 for 2008/2009 is 32.9%. The Universities and Colleges Admissions Service (UCAS) shows 29.2% of the 18 year old pupils applied to universities.

[13]The local polynomial regression is at the degree of one (local-linear smoothing) for better properties a the boundaries (Xie *et al.*,2012(124)). Besides, there is little difference in the result from a local-mean smoothing in our sample.

[14]The participation probability is defined as $P_i = P(D_i = 1|x_i, u_i)$ for individual i. x_i and u_i are observed and unobserved variable respectively. Assuming a logistic distribution, the odds ratio that individuals i and j receive treatment D is $P_i(1 - P_j)/P_j(1 - P_i) = exp(\beta x_i + \gamma u_i)/exp(\beta x_j + \gamma u_j)$. Becker and Caliendo (2007)(13) shows the bounds of the odds ratio as $(1/e^{\gamma}, e^{\gamma})$. If there is no hidden bias, γ is zero. The critical value e^{γ} is the measure of the degree of departure from the case free from hidden bias.

[15]The radius matching is only technically different from the main matching results. Thus, I compare the simulation results with its own generated benchmark at the first step.

Chapter 3

Electronic Games and Children's Cognitive and Noncognitive Development

3.1 Introduction

Coupled with increasing digitalization, electronic games have rapidly become part of children's culture. Some researchers state that children may be particularly susceptible to the influence of video games (Bushman and Huesmann 2006(19); Lobel *et al.,*2014(62). The impact of playing electronic games on children's development remains a focus of debate. On the one hand, electronic games have been widely investigated concerning their association with aggression and violent behaviours (e.g. Anderson *et al.,*2010(4)). On the other hand, there has been an increasing line of research with a focus on beneficial sides such as creativity (Jackson *et al.,*2012(70)), visual attention skills (Boot *et al.,*2008(17)), spatial skills (Durkin and Barber 2002(39)), and prosocial behaviours (Ewoldsen *et al.,*2012(43); Dolgove *et al.,*2014(36)).

The topic has been mostly discussed in psychology and health sciences outside the field of economics. Relatively few studies in economics concentrate on electronic games. Using a large sample of Longitudinal Study of Australian Children (LSAC), Fiorini (2010)(53) looks at the impact of time spent on console video games on a set of skills. Although the main focus is on general computer usage, the results reveal that playing video games has a positive impact on non-verbal intelligence test scores among children aged between approximately five and seven years old. While for noncognitive skills such as restlessness, social skills, and emotional problems, the evidence is mixed, and the influence seems to vary with children's age and their position in the skills distribution. Drawing inference from the same dataset, Fiorini and Keane (2014)(54) suggest that time spent on media (TV and computer) does not lead to worse developmental outcomes. For example, for reading skills, it is at least as productive as time in school care. More recently, Fairlie and Ariel (2017)(47) conducted a field experiment that randomly provides free computers to more than one thousand children attending grades six to ten in high school in California. Their findings show that children in the treatment group have a tendency to have a social networking site and to interact with friends in person as well, which suggests a positive impact of computers on social capital development.

The only research specific to electronic games in economics is conducted by Suziedelyte (2015)(116) who uses a fixed-effects model to test the effect of video games on standardised measures of children's cognitive and noncognitive skills. Using the Panel Study of Income Dynamics (PSID) and Child Development Supplement (CDS) data, the author estimates the impact of time spent on video games, with controls for other time inputs such as watching TV and reading, and family background as well. The main finding is that an increase in game time improves students' ability to apply mathematics knowledge to problem-solving. Nevertheless, there is no evidence of a detrimental impact on children's behavioural problems.

Taken as a whole, the current literature addressing the impact of electronic games shows inconsistent results. This may reflect the validity of research designs and settings, and empirical methods. Arguably, much of the video game research has not adequately addressed the populations of interest to the general public. Most small-scale experimental studies recruit college participants, and produce results that might be vulnerable to small sample sizes and inadequate pre-test controls. By contrast, the effect of playing video games is often smaller as more control variables are included in models, and results from larger longitudinal data do not reveal strong associations.

This study aims to shed light upon this issue but has a different focus on early childhood skills. The contributions could be outlines in three main aspects. First, this study captures the early effect of video games before the amount of play increases until stable patterns merge during middle childhood and adolescence, but around a sensitive period when children are experiencing many physical, cognitive and emotional growth that provide some preliminary conditions for video games. Studies have found that early childhood skills are important predictors for later life outcomes (Murnane and Levy*et al.,*1995(90); Keane and Wolphin 1997(73); Cameron and Heckman 1998(21),2001(22); Cunha *et al.,* 2006(27)). There has also been growing interest in the determinants of cognitive and noncognitive skills, with a different focus on children's activities, child care, parenting styles, and other family factors (Fiorini and Keane 2014(54)). It is recognised that early childhood intervention programs have a long-lasting effect on education and labour market outcomes (Heckman *et al.,*2006(66)). It is worth investigating the potential influence of electronic games given their increasing prevalence in children's lifeworld.

Second, more peers or school-level factors might obscure the relationship between gaming behaviours and personal development in a sample of adolescents when it comes to empirical analysis. For instance, a strict school may affect one's leisure activities and some noncognitive traits such as self-control and perseverance. Simultaneously, social and academic peer effects may contribute to student's development. Therefore, this paper focuses on young children as parents and family environmental factors play an important role in early childhood.

Third, from an educational standpoint, early childhood education often focuses on learning through play, especially cognitive gains (Frost *et al.,* 2001)(56). This study evaluates a general form of digital play and finds no evidence of a detrimental impact of playing electronic games on children's early development between age three and five. Instead, there is some evidence that gaming promotes cognitive processing and alleviates emotional, peer problems for young children. Since there is no official UK guidelines[1] on screen time, and this paper provide relevant evidence to this time guideline in a way. To my knowledge, this paper is the first UK's evidence on the causal relationship between electrical games and young children's skills development based on large social survey data.

The dataset used is the recent Millennium Cohort Study (MCS) which has been tracking UK children born between September 2000 and January 2002. In this paper, using detailed information on the children and family characteristics, I first adopt both linear and Poisson estimation to reveal the potential association between video games and cognitive and noncognitive skills based on a Value-Added Model (VAM) which includes a measure of past achievement to help compare the value-added to the human capital accumulation. Then I use an instrumental variable approach to address the issue that digital gaming behaviour is likely to be correlated with unobserved parental inputs, individual attributes and preferences.

The primary identification approach relies on variation in mother's computer usage and internet access at home. The first-stage relationship is statistically significant at the one percent level: mother's computer use at home in children's born year increases the likelihood of children's playing pc game by 8.6 percentage points; the acquisition of internet access after children's born increases the likelihood by 7.7 percentage points, conditional on a set of controls for individual and family characteristics. In addition, I adopt a heteroskedasticity-based instrument and Conditional Mixed Process (CMP) to improve statistical inference. In practice, the estimates are not profoundly sensitive to different choices of subsamples or model specifications.

The rest of this paper is organised as follows. I first outline my empirical method in section two and describe our data in section three. The main empirical results are presented in section four and followed by a few robustness checks. Finally, this chapter concludes with a summary of our main findings.

3.2 Methodology

Following Todd and Wolphin (2003(117), 2007(118)), I specify the estimation equation as a Value-Added Model (VAM). This approach has been widely used to examine the impact of various educational inputs in education production. The basic idea is to include an indicator of past performance at some stage so as to control for the past inputs and innate ability that may not be sufficiently reflected by observed information.

$$Y_{it} = \beta_0 + \theta Y_{it-1} + \beta_1 G_{it} + \beta_2 T_{it} + \beta_3 X_{it} + \beta_4 P_{it} + \beta_5 P_{it-1} + \beta_6 F_i + \varepsilon_{it} \quad (3.1)$$

Y_{it} is the outcome variable measured at time t for individual i. G_{it} is the time spent on playing digital games at time t for individual i. T_{it} is the time spent on other activities such as watching TV, reading and physical exercise as there are substitutions between various activities given time constraints. X_{it} includes a set of time-invariant variables such as gender, ethnicity and birth weight, and controls for age, health status and school/childcare attendence. P_{it} measures parental input at different ages such as various activity involvement in children's life. In the absence of evidence on the declining impacts of observed historical inputs, I, therefore, incorporate them as well. All past and contemporary inputs contribute to children's development, and this framework captures the cumulative nature of development. F_i controls for family factors, such as socialeconomic class, highest qualification held by mother, family income, and structure (the presence of parents and siblings). The lagged outcome Y_{it-1} is included to capture the impact of endowment or innate ability. This is assumed to follow a geometrical declining path at a rate of θ in a standard linear specification (Todd and Wolphin, 2003(117)). In a non-linear setting such as a Poisson model, the lagged outcome Y_{it-1} included to estimate the conditional mean, which helps capture the inner persistence of skills development. ε_{it} is the error term. This specification emphasises a contemporaneous relationship between playing digital games and cognitive and noncognitive achievement.

Several identification challenges arise. First, it is hard to obtain perfect proxies for all cumulative inputs given data limitations common to longitudinal research. Mostly, inputs are measured at different discrete time points. It is hard to tell whether inputs at measurement time reflect consistent parenting styles or just a specific contemporary report. Furthermore, parents might adjust their parenting according to children's performance in general, which gives rise to endogeneity of parental inputs. Second, digital playing, the variable of interest, is potentially endogenous for a variety of reasons. For instance, children confronted with more severe peer problems might choose to play more games as an escape from depressing realities. It is challenging to capture inner motivations of playing electronic games, which results in potential simultaneity bias in estimation. Third, measurement error exists in inputs and outcome variables. Many family inputs such as reading to children are based on maternal reports and may be strategically reported. In another sense, these measures can be endogenous as better quality parents are the most probable to have better awareness of their parenting activities and children's behaviours.

All in all, credible identification requires orthogonality between unobserved inputs and individual characteristics, observed inputs and past outcomes. The OLS estimates are biased and inconsistent as a result of omitted variables or reverse causality if a correlation exists between the error term ε_{it} in the achievement equation (3.1) and the playing digital games G_{it}. Previous research based on large social survey datasets is predominately cross-sectional in nature and can at best be viewed as reporting conditional associations. In this paper, I primarily adopt an instrumental variable approach aimed at isolating the variation of children's digital playing caused by exogenous variation in access.

Specifically, I outline the two stages as follows:

$$G_{it} = \phi_0 + \delta Z + \phi_1 Y_{it-1} + \phi_2 X_{it} + \phi_3 P_{it} + \phi_4 P_{it-1} + \phi_5 F_i + \epsilon_{it} \quad (3.2)$$

$$Y_{it} = \gamma_0 + \vartheta Y_{it-1} + \rho G_{it} + \gamma_1 X_{it} + \gamma_2 P_{it} + \gamma_3 P_{it-1} + \gamma_4 F_i + \upsilon_{it} \quad (3.3)$$

X_{it} is a vector of children's observed characteristics. F_i and P_{it} represent family background and parental inputs. Y_{it-1} is a control for past cognitive and noncognitive performance. ρ is the parameter of interest that measures the impact of playing digital games on cognitive and noncognitive scores. The set of excluded instruments Z includes: a dummy variable indicating whether natural mother uses a computer at home at the birth year of the cohort member; an indicator for new acquisition of internet access in household after children's birth. These two instruments are intended to capture the impact of ICT access on children's gaming. Further discussions are as follows.

As documented in MCS, approximately 32% of mothers neither use a computer at work or home. Around 51% use a computer at home. Some qualitative studies[2] discuss the relationship between computer attitudes, self-efficacy, and usage of parents and their children (Levy 2008(79)). In the absence of a sound theoretical foundation for such an intergenerational impact, I propose three possible links. First, parental computer usage may crowd out some computer time for children, conditional on one computer per household in most cases. Second, especially young children are shown to imitate parents' activities in some way, which has been widely discussed in psychology literature. If parents use a computer very often at home, children might get more curious about or familiar with computers early. Third, parents with more computer experience may hold more flexible and positive views of computer usage. These parents might allow for more frequent computer usage when they are better able to intervene in the child's use of computer or other online activities.

The second instrument is a indicator of new acquisition of internet access after children's birth to supplement the information of ICT access in the household during the subsequent five years after children's birth. The household internet access is generally compatible with a pc access. In MCS, around 65% of mothers who reported their pc use at home were also connected to the internet at home. Only 47% of households reported that they had an internet connection at children's birth year. This figure of internet access has increased to 61% in 2003 when the children were three years old. In total, around 34% of households in our working sample obtained internet access after children's birth.

The validity of IV estimation is dependent on whether these two instruments have any direct impact on children's cognitive and noncognitive outcomes. The association between the instruments and outcome variables has to be exclusively attributed to the correlation between the instruments and endogenous variable, after controlling for other covariates. Regarding internet access, the instrument would be called into question if children's latent characteristics or gaming preference play a role in a family's decision over internet installation. I ran a few separate logistic regressions on the new acquisition of household internet connection across different MCS waves, and found no statistically significant relationship between children's past cognitive/noncognitive skills or health condition once family's characteristics are controlled for. Only family's characteristics such as mother's NVQ, SEC, drinking behaviour, household income are strong predictors of new internet access. Findings are similar when it comes to mother's pc use. Particularly, mother's computer usage is closely related to their education and working condition as shown in Figure 3.3: mothers with higher National Vocational Qualification (NVQ) Level have a higher likelihood of using a computer at home. These results are considered to support the independence between family's pc/internet access and children's gaming activity. In this paper, I include rich controls for many children and family features to enhance the validity of the exclusion restriction, and further robustness checks are provided in subsequent section.

As an alternative identification approach, I use Lewbel's (2012(80), 2018(81)) IV estimation that takes advantage of the heteroskedasticity in the error term in the first-stage equation. This IV approach introduces $(X - \overline{X}) * \widehat{\epsilon}$ as the instruments that contribute to identification when strict exclusion condition might not be satisfied. The choice of X could be all the explanatory variables or a subset of them. The $\widehat{\epsilon}$ is the residuals from the first-stage regression. The Lewbel (2012(80), 2018(81)) shows that a consistent identification of the parameter of interest could be realized by having regressors that are uncorrelated with the product of heteroskedastic error. Specifically, the identification rests on two assumptions $cov(X - \overline{X}, \epsilon^2) \neq 0$ and $cov(X - \overline{X}, \epsilon * v) = 0$. The first one states the existence of heteroscedasticity in the first stage and ensures the correlation between instrument and endogenous variable. The later one is satisfied if the mean zero error processes are conditionally independent. Error correlations exist in many models due to unobserved common factors. In our setting, the common factors could be measurement error, latent personality or preference for electronic games. The variability of gaming among certain groups may be greater than other groups, and Lewbel's approach exploits these distributional differences that potentially capture children's gaming preference or other unobservables. I only chose relatively exogenous variables such as ethnicity, country, urban and mother's age at children's birth to construct heterogeneity-based instruments.

It should be noted that the original variable that documents digital playing is a categorical variable indicating different ranges of gaming hours - this might make the first-stage estimation weak and biased if we regress on the assigned mean values of gaming hours in each group. To allay this concern, I employ the Conditional Mixed Process (CMP) proposed by Roodman (2011)(101) to better estimate the potential non-linear effect of gaming hours on children's development outcome. A system of clearly defined stages could be set up based on theory and research context. Some dependent variables may appear in the right-hand side of other equations. CMP could fit these multi-stage equations by proposing a link function between their error processes, and then jointly estimates independent variable coefficients via simulated maximum likelihood. It is primarily built up in the framework of seemingly unrelated regressions but has expanded the classical regressions of continuous dependent variables to more flexible settings. CMP makes for modelling phenomena that latent variables can be linked to the observed variables in multiple models, especially when multiple and diverse models need to be combined with multiple types of variables such as binary, ordered, categorical, truncated and censored data. In the application of data, the first stage could be estimated as an ordered-probit model that makes no assumptions of the interval distance between each option.

3.3 Data

The present research is based on the Millennium Cohort Study (MCS) which tracks a cohort of children born in the UK between September 2000 and January 2002. It contains rich information regarding children's cognitive and noncognitive development, children and maternal health, parents' employment and education, parenting and schooling choice *etc.* 20,646 families were originally contacted and the parents of 18,552 families successfully took the first interview when the cohort children were nine months old. The follow up face-to-face surveys were conducted when children were aged three, five, seven and eleven years old. In the survey, around 99% of the principal respondents were biological mothers. Some new families entered the survey in wave two, but I restrict the sample to the same families and main parent present across all the first three sweeps, 13,107 families in total. 88 families with twins or triplets were excluded. The final sample of this study includes 7,552 observations with complete information in covariates[3].

3.3.1 Cognitive and Noncognitive Measures

Cognitive development is measured using the British Ability Scales (BAS) that includes a set of tests for children aged from two to seven years eleven months old. Six different BAS tests have been administrated across MCS sweeps by a trained interviewer: Naming Vocabulary, Word Reading, Picture Similarity, Pattern Construction, Bracken School Readiness Assessment and Progress in Maths test. These tests were not repeatedly conducted across waves. The vocabulary score was repeatedly measured in wave two and three; picture similarity and pattern construction were measured in wave three - these three measures were examined in this analysis. To illustrate, the vocabulary test is a verbal scale for children aged two years and six months to seven years and eleven months and assesses the spoken vocabulary of young children by asking children to name the objects in a booklet of coloured pictures. This test mainly reflects the spoken vocabulary of and general knowledge of children and may also reflect the ability to attach verbal labels to pictures. BAS pattern construction test assesses spatial problem solving, dexterity and coordination. In this test, children construct a design by putting together flat squares or solid cubes with black and yellow patterns on each side. The BAS picture similarity tests the problem-solving abilities of the children who are asked to find out the most similar picture following the given four pictures. MCS provides three different scores[4] for these test, and I use the age-adjusted scores which are computed using the BAS manual's conversion tables.

Psychosocial adjustment of children was reported by mothers using the Strengths and Difficulties Questionnaire (SDQ), a widely used behavioural screening instrument for children between three and sixteen years old (Goodman 2000(58)). The SDQ is filled out by parents and contains five main scales: Emotion Symptoms, Conduct Problems, Hyperactivity, Peer Problems and Pro-social Scale. Parents were asked to comment on a set of statements with: Not true, somewhat true or certainly true, counted as zero, one or two points respectively. The sum of all points in the first four scales (excluding pro-social scale) gives the total noncognitive difficulties in general. The SDQ total difficulties range from 0 to 40, and the higher score is intepreted as worse behavioural problems. The score of pro-social scale differs from the score of other noncognitive difficulties and has been argued to be different from other psychological difficulties (Goodman 2000(58)). A higher score represents a better outcome. In this paper, I focus on the total SDQ score and present results for all five subscales as well. The scores could be considered as count data in a way and are generally right-skewed (see Figure 3.1). Therefore, I further specify a Poisson distribution for estimation.

3.3.2 Electronic Games

Playing electronic games on computers or game consoles is reported by parents when the children were five and seven years old. There are also reports for other screen time such as watching TV or video. The measures are exposure time on a typical weekday during the term-time on a six-point scale: none, less than 1 hour, 1-3 hours, 3-5 hours and 5-7 hours and more than 7 hours. In the original survey, around one-third of children did not play games on a computer or console at age five. The average is around 0.74 hours and is higher among boys than girls. One limitation is the lack of a separation between playing electronic games on computers and other game systems before age eleven (reported after wave four). Around 76% of children play no more than one hour on a regular weekday. 21% of children have a gaming time between one to three hours. Around 1% of children, 70% of them are boys, have an excessive gaming time more than five hours. For the millennium cohort in our analysis, the game playing was more based on console platform (Nintendo-DS and Play Station 2, Xbox) . For examples, the top five video games[5] in Europe in 2006 were *Nintendogs* (simulation), *Brain Age* (Misc), *Supermario*, *Animal crossing* (simulation),*Mario Karts* (racing). Representative PC games were *Grand Theft Auto*, *the Sims 2*, and *World of Warcraft etc.* At this time, electronic games were not substantially different from many current game models, and the manufacturers were continuing improving graphical expression (more advanced 3D graphics) and story-telling. It was a period before the expansion of popular massive multiplayer online gaming (MMOGs) and casual games based on smartphones or tablets. But MMOGs are still demanding in terms of features in online socializing and gaming strategy for most young children before age five.

3.3.3 Family Background and Parental Inputs

Both cogntiive and noncognitive skills are suggested to be related to family backgroud and other characteristics of the home envrionment (e.g. Carneiro *et al.,* 2007(23)). In this paper, a set of typical controls for family background are controlled for such as mother's[6] social economic classification (SEC), national vocational level (NVQ) and household income. As shown in Table 3.1, 36% of mothers do not work at the time of interview and around 67% of them were consistently not in work across the first three MCS waves. Other maternal characteristics such as age, BMI, smoking/drinking habits, and mental health (whether has depression) are also included as essential controls for genetic influence and the current maternal health conditions that might affect parenting behaviours. 36% of mothers reported depression ever during the first three years after children's birth.

There are a variety of measures that are similar to those in the "Home score" which is often used in the US studies to capture parental inputs. Melhuish *et al.,*(2008)(89) discuss different home learning variables such as reading to child, and other routine activities (regular bedtime). In MCS, there are consistent records of parenting including the frequency of reading to children, doing musical/physical activities and going to library etc. These measures of parent-child joint activities are typically described across five or six frequency scales from "never" to "every day". In our main regressions, these ordered categorical variables are transformed into standardised measures by Principal Component Analysis (PCA) to better reflect a general parenting pattern. Our constructed measures disentangle activities at age three and five, the reading-relevant activities and other indoor activities (see Appendix Table 3.12). In addition, I incorporate the Child-Parent Relationship Scale (CPRS)[7] (Pianta 1992(97)) which is a self-report instrument completed by mothers or fathers. It assesses their perceptions of their relationship with their son or daughter. Scale ratings can be summed into groups of items corresponding to conflict and closeness subscales. Also, the family completeness (whether both parents live in the household) is considered for the sake of its role in developing children's social competence. Essentially, these parental inputs variables are included as proxies for general parenting patterns in the early childhood. It is less likely that children's digital playing is so excessive before age five that parents adjust their general parenting disciplines.

3.3.4 Other Covariates

The vector X_{it} contains many individual characteristics such as gender, ethnicity and countries. 91% are white and 63% live in England. The average age of the working sample is five and three months. Age in months and its quadratic form are included to account for potential non-linear time trends of children's development. For cognitive skills, the age-adjusted T-score is standardised within a three-month range, and we still need to control for age variation within this range. I also include the number of siblings at home to account for a dispersed family resource. Children's health status is controlled for by standardised birth weight and an indicator of long-standing illness. In our working sample, around 6% of children have a birth weight under 2,500 grams. These controls are fixed at the time the video gaming behaviour is determined.

Apart from these, I include information about children's other activities such as the hours of watching TV on a weekday, days of doing sports per week because children might substitute among various activities given time constraint. These behavioural variables help control for the unobserved confounder such as leisure preferences or specific personality, and confound the solely effect of playing video games. Further discussion about these activities are also provided in the section of robustness check.

Students' school and childcare attendance are controlled for because of their correlation with children's development and leisure activities. Extra bias might be introduced if video gaming at age five determines some of these control variables, especially some variables measured at age five. In our sample, over 90% children did not start child-care attendance after age four, suggesting more effects from parents themselves. Similarly, over 95% children have enrolled in full-time education in our sample and there is a statistically insignificant correlation between children's behaviours and school attendance. It can be argued that influential factors behind these covariates are more captured by family background and general parental inputs.

3.4 Results

3.4.1 Impact on Noncognitive Outcome: OLS and Poisson Estimation

Table 3.2 presents results from ordinary least square(OLS) estimation of the impact of playing digital games on the total noncognitive difficulties measured by SDQ. In the first column, the unconditional relationship between playing digital games and noncognitive difficulties is negative and statistically significant at the one per cent level, but the explanatory power is limited. The correlation remains statistically significant when basic demographic controls such as gender, ethnicity, age, country are included in the model. Then, the inclusion of past noncognitive and cognitive outcomes reduces the coefficient of playing electronic games by almost half in magnitude. The past SDQ score accounts for roughly half of the current performance suggesting the long-memory of noncognitive problems. There also exists interactions between cognitive and noncognitive development. In (4) and (5), I include controls for the health condition and other activities, the negative association between digital playing and noncognitive difficulties is slightly changed and is statistically significant at the one per cent level. As I include more controls for family and parents, the coefficient of digital playing remains stable and suggests that playing electronic games is correlated with around -0.064 of a standard deviation reduction in SDQ score on average - improved performance in noncognitive problems. This result is also consistent with the measure in raw SDQ score - an average decrease of 0.293, as shown in (9). Table 3.2 only selectively presents the coefficients of some covariates of interest. Consistent with our expectation, the indicator for the health condition, the standardised birthweight, is statistically significant in predicting current noncognitive difficulties. In addition, maternal depression and physical health condition (standardised BMI at children's birth) are strong predictors for children's current noncognitive status. The coefficient of household completeness is also consistently positive and statistically significant, suggesting an ineligible impact of single-parent household in children's social development.

Noncognitive development may manifest the property of self-generation and therefore does not follow a linear trend. The original noncognitive test scores are right skewed (see Figure 3.1), and around 80% of children in our sample fall in a score range between 0 to 14, a range normally considered average[8] . Moreover, the noncognitive measures are based on maternal reports about different degrees of problematic behaviours, with assigned scores from 0, 1 to 2. This reflects the frequency count of the behavioural problem in some sense. To better fit these data features, I use Poisson regression to estimate a more interpretable effect. This supplements the relative comparison provided by OLS that is based on standardised scores. The results are summarised in the last three columns in Table 3.2 and show a consistent pattern. The following Poisson regression shows that the average marginal effect of playing electronic games is a 0.286 point reduction in behavioural problem scores. In (11), I present the result of Negative Binomial estimation with a quadratic variance function to account for original dispersed data of noncognitive difficulties. The consistent estimation hinges on the correct specification for the variance function parameter α. The estimated parameters only slightly differ from those of the Poisson estimates. The empirical model in (12) further considers the dispersion parameter α as a linear function of age, gender and birth weight. In general, the estimates do not change substantially and indicate a negative association at the one per cent significance level. I calculate $(\hat{y}/y)^2$ as a more direct measure of model fitness, and Poisson regression is slightly superior compared to other two Binominal models. Ultimately, I choose the Poisson as our preferred model for non-linear estimation as the Binominal models might be sensitive to the estimates for variance function.

When it comes to the division of internalising (emotion and peer) and externalising (conduct and attention) problems, some associations appear in emotion and peer problems as shown in Appendix Table 3.13. These associations might be partially explained by the fact that some specially designed electronic games help with social contact and cooperation. Playing digital games is associated with a reduction of 0.08 of a standard deviation for emotional problem score, suggesting potential improvement from emotional relief. For externalising problems, the baseline association is statistically insignificant. These results accord with the general discussion about the inner motivation of playing digital games, as some children may find themselves better off in a virtual world.

3.4.2 Impact on Noncognitive Outcome: IV and CMP Estimation

As shown in the previous section, I find a robust association between playing digital games and noncognitive development. However, there might be omitted factors that affect both digital playing and children's development - bringing difficulties in causal inference. Consistent and unbiased estimation requires an orthogonality condition between the error term and potentially endogenous digital playing. To address these concerns, I use parental computer use and new household internet access as instruments that are more correlated with an effect of general ICT access on children's gaming behaviours. Our estimated local average treatment effects (LATE) help capture the early and natural exposure of electronic games among young children before they formalize a strong preference for digital games or exhibit addiction. Besides, many parents are also cautious in managing video games time for their young children before age five, and our LATE is useful in providing instructive information for early children development.

The first two rows of Table 3.3 show the main first-stage relationship indicating that children whose mother uses a computer at home are 8.6% more likely to play computer games; new internet access at home increases this likelihood by 7.7%. The exclusion condition requires that instruments only affect the outcome variable exclusively via its effect on the endogenous variable of our interest. In our sample, it is assumed that mother's pc use and new household internet access have no direct effect on children's cognitive and noncognitive outcomes conditional on parental and family's characteristics. Table 3.3 presents regression results about the potential correlation between our instruments and other covariates that may be related to other unobserved inputs or children's characteristics. For instance, it is very likely that some common unobserved factors drive children's time spent on screen entertainment such as TV and computer. Our instruments, however, hardly affect the time spent on TV, or other time inputs such as doing sports. Also, there is an insignificant impact of our instruments on children's sleeping problem, family inputs such as reading to children, having many family rules and good home atmosphere, conditional on controls for other family and parents characteristics. These results show supportive evidence that our instruments do not affect children's development outcomes through other channels.

Panel A in Table 3.4 presents a series of IV estimations of the impact of playing digital games on standardised noncognitive difficulties. The first column shows the baseline OLS estimate suggesting that playing digital games is associated with a reduction in SDQ score of 0.064 of a standard deviation. The IV estimates in column (2)(3), using two-stage least squares and two-step GMM are imprecise and larger than the value of OLS estimates in absolute magnitude. The coefficient of playing electronic games becomes statistically insignificant.

Concerning the strength of our instrumental variables, a test on excluding our potential instrument from the reduced-form equation yields an F-statistic of 31.25, and Shea's partial R^2 obtained from regressing the dummy of whether playing digital games on our instruments has a value of 0.009 once common exogenous variables are partialled out. The Hansen's J statistic cannot be rejected at any reasonable significance level, supporting the exogeneity for the set of instruments. The IV estimates also pass the test for overidentifying restriction. In (4), limited information maximum likelihood (LIML) estimation is conducted to better tackle the potential problem of weak instruments, and there seems to be limited improvement.

As an alternative approach, the Lewbel's IV method based on heteroskedasticity is reported in the specification (5). For the first-stage regression, the statistic Breusch-Pagan test of heteroskedasticity is 101.62, and the null hypothesis of the homoskedastic errors can be rejected at the one per cent significance level. Then the set of instruments $(X - \overline{X}) * \widehat{\epsilon_{it}}$ is applied in identifying the causal impact of playing digital games. The choice of variables[9] for Lewbel's IV are restricted to those variables predetermined before children's birth such as ethnicity, country, urban indicator, siblings and mother's BMI at children's birth. This IV estimate suggests that the impact of playing digital games has a statistically insignificant impact on children's noncognitive performance.

The Panel B of Table 3.4 presents results about the impact of gaming hours. I assign the variable of gaming hour by the interval mean according to the original categorical data. The estimates in (6) and (7) have a negative sign but are statistically significant. The OLS estimate in column (6) suggests that one more hour spent on electronic games is correlated with a reduction in noncognitive difficulty scores by 0.011 of a standard deviation. The F-statistic becomes 14.79, which stems from the more limited variation in the first-stage. The Lewbel's approach (8) increases instrument strength and is more efficient, but generates similar results.

In our sample, gaming time on a weekday ranges up to even more than seven hours. Although the literature has not provided a clear recommendation for a safe gaming time, psychological research suggest associations between excessive gaming and negative consequences in health, social life and school performance (e.g. Ng and Wiemer-Hastings,2005(92); Lemmens *et al.*,2009(77)). A large amount of screen time virtually occupies one's leisure, crowding out other activities such as reading, socializing and sleeping. Moreover, the mean regression on gaming hours using assigned interval mean value might be biased if the gaming time actually does not evenly distributed within each interval. To better examine the potential different impact of gaming hours, I further change the variable into three categories and estimated their effect on the standardised total noncognitive difficulties.

Compared to the group with no game playing, it appears that a moderate gaming time, i.e, no more than three hours per weekday, has a positive impact on improving noncognitive performance. Owing to a lack of strong instruments for these three category variables, I use Conditional Mixed Process (CMP) to estimate the impact of different gaming hours by setting the first stage as an ordered probit model. By allowing the correlations between the error terms of the two stages specified in the earlier section, CMP adjusts the estimates and shows a similar outcome as presented in (10). The parameter of the correlation between the error terms is 0.058, and a significant cut-off point in the latent utility of playing electronic games appears at three hours. However, the existent heteroskedasticity in our second stage estimation about the impact on standardised SDQ score may render consistency, which relates to the assumption on the jointly normal distribution of errors. As a result, CMP results are regarded as suggestive evidence of the signs of the coefficients of our interest.

3.4.3 Impact on Cognitive Outcome

The same estimation is repeated in examining the impact of playing electronic games on cognitive development, measured by "Naming Vocabulary", "Pattern Construction" and "Picture Similarity". Contrary to noncognitive measure which is based on behavioural problems, a higher cognitive score represents better cognitive development. Table 3.5 presents the results and suggests a positive impact of playing electronic games on cognitive development. Playing digital games is associated with a 0.11 and 0.08 of a standard deviation increase in aspects of pattern construction and picture similarity respectively. The IV estimates are statistically significant, larger and positive. Intuitively, video games require some attention skills and cognitive processing that can be exercised in a way. These results provide suggestive evidence of a positive impact on cognitive skills and no effect on noncognitive development.

3.4.4 Heterogeneity

3.4.4.1 Gender

Boys and girls tend to behave differently, might have biologically different cognitive and noncognitive development trajectory, and may interact with technology in different ways. While boys and girls score roughly the same on many cognitive abilities and have different comparative advantages, girls consistently have a higher score than boys in many aspects of social-emotional development.[10] From the upper panel of Table 3.6, it is observed that girls generally outperform boys in their cohort in almost all development scores. In terms of activities, more boys are reported to play electronic games than girls, but the gap difference is not large, around 8%. Results presented in the lower panel of Table 3.6 demonstrate no negative impact of playing electronic games on noncognitive skills, which is consistent with our main results. A positive impact on cognitive development, however, only appears to be evident among girls. There is a chance that a higher cognitive and noncognitive level influences the effect of playing electronic games complementarily among girls. At the same time, the potential cognitive benefit might be undermined by more noncognitive difficulties among Boys.

3.4.4.2 Family Background

Family environment is one of the most influential factors in early childhood development (see discussion by Currie and Almond 2011(28)). I separate children in terms of family income and mother's highest NVQ level. The noncognitive outcomes vary across these different groups: the average SDQ score is 8.2 in the income group of the lowest 25% quantile, which is almost 50% higher than that in the top 25% income group (see Table 3.7). A similar difference is observed across different NVQ groups. But this disparity is small for pattern construction score. As for the ICT use, mothers who use a computer are more prevalent among these higher income or NVQ level. 70% of children play electronic games, but the gaming time decreases by income group. On average, it is 0.88 of an hour for the lowest 25% income quantile group and 0.61 of an hour for the highest 25% group. These trends suggest effects of parenting and family background. As shown in Table 3.7, IV estimates across these groups are less precise because of a reduced sample size, but OLS estimates suggest a quite similar positive association between digital playing and cognitive performance whereas the relationship regarding noncognitive skills does not show a clear trend.

3.4.4.3 Cognitive and Noncognitive Level

Human capital literature characterizes skill formation by two important features: self-productivity and dynamic complementarity (e.g. Cunha *et al.,*2006(27)). Different skill levels at earlier stage could affect the formation and productivity of investments in subsequent stages. Adding interaction terms in the main regressions helps capture a potential heterogeneous impact by children's initial development status, but it hardly affects our estimates for the coefficient of the digital playing variable. The cognitive interaction term is statistically significant in many cases, and suggests a potential complementary effect in cognitive development. However, the past noncognitive level seemingly has no impact on the estimates of the variable of interest.

I further divide our sample by different levels of children's cognitive and noncognitive score measured at age three. Table 3.8 summarize relevant results. By noncognitive level, for the normal group (80% of our sample), the OLS estimates show an association with a 0.06 of a standard deviation in the reduction of total

SDQ score and 0.11 of a standard deviation increase in the pattern construction score. Both are statistically significant at the one per cent level. While the other two groups with notable behavioural problems, the OLS estimates seem higher in pattern construction, and the IV estimates become less precise. By cognitive level, it appears that the low-end children might benefit more in noncognitive development, but the situation is opposite in terms of pattern construction.

To sum up, it is less clear how noncognitive level might affect the impact of playing electronic games. By contrast, children with higher cognitive abilities seem to receive more benefits of electronic games. Moreover, cognitive and noncognitive skills may exhibit different development features, and their interactive relationship between them needs further exploitation.

3.5 Robustness Checks

Having found a positive impact of playing electronic games on children's cognitive skills and an insignificant impact on noncognitive skills, I next perform multiple robustness checks to verify my findings. One maintained assumption of a valid instrument is the exclusion condition, but it is naturally not testable. Therefore, I check the sensitivity of the estimates in alternative samples that might have other confounders correlated with our instruments. Also, I check the stability of our results to different model specifications.

3.5.1 Maternal Characteristics and Parenting

Our instruments might relate to other influential factors in children's development, especially parental factors. I test this possibility by exploring several subgroups featuring in different maternal characteristics and parenting behaviours. In the first subgroup in the upper panel of Table 3.9, the sample is restricted to the group of mothers who reported good health and no depression ever. This follows a concern over the intergenerational impact of maternal mental health on children's health and psychological development (e.g. Murray *et al.,*(1997)(91), Goodman and Gotlieb, 1991(59)). Although the IV estimate about the noncognitive aspect shows an opposite sign, the estimate of cognitive impact is consistent to our main regressions. The next group only includes those mothers aged over 25 because of their higher possibility of having a steady job and income. Thus, they are inclined to settle down and purchase household goods such as a desktop computer. This relationship is empirically supported by a separate regression on the determinants of mother's home computer use. However, this is unlikely a major problem because teenager mothers only take 5% of the working sample. Excluding the potential impact of young mother does not affect the estimates of the effect of playing digital games much.

It could possibly be argued that more educated parents might have better parenting competence or be better at disciplining children. Although I have included many controls for parenting activities, I present an additional check on subgroups of parents who have rules over TV watching time and those who reported above-average parenting competence. The OLS and IV estimates in these groups in the upper panel of Table 3.9 are close to our baseline estimates, which helps alleviate the concern over better supervision and instruction of children's digital usage from more competent parents.

3.5.2 Other Activities and Individual Characteristics

In the lower panel of the Table 3.9, I check whether our results are sensitive to individual characteristics that might affect digital playing and cognitive or noncognitive outcomes. The first check is children's health status that may directly constrain their daily activities. This sample includes children who have an obesity problem or other illness that affects daily activities according to mother's report. T-tests do not suggest a significant difference among a range of activities but a significant disadvantage in noncognitive and cognitive tests. Similar to the first group in panel A of Table 3.9, the estimates only support a positive association between digital playing and cognitive development rather than any relationship with noncognitive improvement.

Second, it is of necessity to consider the intercorrelations between different activities that might be closely related to unobserved preferences and substitution activities. In our sample, the hours playing electronic games are positively correlated with TV hours and negatively associated with the day playing sport. This association is statistically significant at the five per cent level. Therefore, I separately test our outcome in an alternative sample of children who had their own TV in their bedroom at age seven. The presence of a TV in children's bedroom could be linked to children's characteristics such as a preference for screen entertaiment or video games based on console. In this group, the IV estimate shows an opposite sign in terms of noncognitive difficulties. Then, I set samples with more common TV and sports time - over 65% of children fall in this range, and find results similar to main regressions. The estimated coefficient for the hour of watching TV is statistically significant at the 10% level and suggests a negative impact on children's development while doing sports shows a persistent positive impact in our regressions. Moreover, in models without controls for these activities, the OLS and IV estimates are -0.061 and - 0.114 respectively and are only slightly affected. These results are also in line with some findings that computers do not displace other after-school activities such as TV watching, reading or sports (Fiorini and Keane, 2014(54); Fairlie and Areil, 2017(47)).

3.5.3 Specifications Checks

There are different statistical models to estimate the production function for children's cognitive and noncognitive development (Todd and Wolphin 2003(117), 2007(118)). Since the primary objective of this paper is not to precisely model cognitive or noncognitive function, my main specification is a value-added model that is preferred in the paper by Todd and Wolphin (2007)(118) for the sake of minimized out-of-sample root-mean-squared error (RMSE). In this section, I examine the robustness of our results to other specifications, as shown in Panel A of Table 3.10. The first specification (referred to "CT") is one with only contemporaneous inputs and characteristics. The consistency of the estimates of the impact of playing electronic requires the orthogonality between the residual terms and the variable of our interest. This is probably achieved by including a rich set of observed controls to reduce the omitted variable bias. In our sample, the OLS and IV estimates are larger in absolute value, which might reflect insufficient controls for omitted confounders.

The second is a first-difference specification (referred to "FD") that differences out time-invariant confounders rather than attempt to control for them. The key assumption here is a time-constant impact of omitted variables. In our analysis, the first-difference of noncognitive outcome is measured by $Y_{t-1} - Y_t$ and refers to the reduction of noncognitive problems; the measure is opposite for the cognitive score with consideration for interpretation. The FD estimates are statistically insignificant. For one thing, this is perhaps due to the diminishing marginal improvement for the most well-behaved children, which is also statistically supported by a significant positive correlation between the past noncognitive problems and the improvement between age three and five. For another, the estimated impact of playing electronic games might vary by latent abilities as a result of the self-productivity in skill formation.

Therefore, I estimate the third specification which relaxes the assumption of a constant impact of unobserved characteristics on outcome variables. Including past performance helps capture the feature of self-productivity, and helps control for the serial correlation of the errors as well. Now, the estimated coefficient shows similar results.

The percent changes in outcomes are used as dependent variables in the last two columns, and the OLS estimates suggest 8.05% reduction in noncognitive difficulties. Comparably, models in the logarithm form of cognitive and noncognitive outcomes yield similar results: playing electronic games is associated with 5% reduction of SDQ score and 2% increase in Pattern Construction score. The IV estimates are 10% for Pattern Construction but are statistically insignificant for total noncognitive difficulties.

In sum, results from these models do not affect our qualitative conclusion about the insignificant detrimental impact of playing electronic games on cognitive and noncognitive performance. Among these four specifications, the VA specification has the lowest RMSE, around 20% smaller than the FD or CT specification.

Panel B of Table 3.10 shows how sensitive of our results are to different sets of control covariates, especially those parenting activities which have been suggested to be important and productive in children's development (Fiorini and Keane, 2014(54)). The inclusion of more parenting variables such as self-rated competence, six-category parenting style, and father-children closeness/conflict relationship scale does not notably affect the estimates. Further, I use the Post-Double-Selection LASSO method (Belloni *et al.,* 2014(14)) to select controls, which has the advantage of allowing for imperfect selection. The number of controls is reduced from 47 to 15, and this procedure mainly excludes some dummies for ethnicity, country, mother's NVQ and SEC. The estimates based on this new set of controls are again close to our main results.

3.6 Conclusion

Based on a large UK longitudinal survey data, the Millennium Cohort Study (MCS), this paper investigates the impact of playing electronic games on children's cognitive and noncognitive outcomes between the ages of three and five. The focus is on young children as they are in a crucial period when substantial development of cognitive and noncognitive skills takes place(e.g. Heckman *et al.,*2006(66); Phillips and Shonkoff, 2000(96)). It is difficult to unravel the causal effect of playing electronic games on children's development owing to non-random variation in individual behaviours. For instance, children may play electronic games to satisfy some inner psychological needs that cannot be well captured by standard questionnaires. To mitigate the endogeneity problem, the primary approach in this paper is to use mother's computer use at home and the acquisition of household internet access as a source of exogenous variation in the probability of playing electronic games among the young children. Despite the correlations between the instruments and family backgrounds such as mother's NVQ, SEC, and household income, a strong first-stage relationship is established once all other covariates about children, parents and family are controlled for. The first-stage F test is around 31 in main regressions suggesting that the instruments are relevant.

The main results of this paper demonstrate no evidence of a detrimental effect of playing electronic games. Instead, I find a persistently positive impact on children's cognitive performance. The association is around a 0.1 of a standard deviation in the tests of pattern construction and picture similarity. IV estimates are larger, positive and statistically significant. This cognitive impact increases by initial cognition capabilities. Regarding noncognitive development, playing electronic games is associated with a decrease of around 0.3 in the original Strengths and Difficulties Questionnaire (SDQ) scores. IV estimates suggest a similar pattern of a reduction but are statistically insignificant. There is no clear gender disparity except that girls may benefit more owing to their relatively better cognitive and noncognitive condition. These empirical results are robust to a range of sensitivity checks on the exclusion restriction of the instruments, and on different model specifications as well. Advantaged family backgrounds do not primarily drive our results.

The strength of this research includes the use of a large observational dataset to control for many families and parental covariates that play essential roles in early childhood development. Furthermore, a range of practical tools is applied to reduce the impact of endogenous gaming behaviour and improve the data-fitting in both linear and non-linear relationships. In line with only few relevant economic literature (Fiorini,2010(53); Fiorini and Keane 2014(54); Suziedelyte,2015(116)), my findings provide new evidence on the absence of a detrimental effect of electronic games among young children. If any, there is a positive impact on cognitive development and a potential mitigation of internalising problems. The noncognitive performance might be less sensitive to children's alternative time allocation Fiorini and Keane (2014)(54), but is more strongly correlated with parental-children relationship. The cognitive benefits more come from reasoning abilities such as pattern construction rather than vocabulary, which is also in consistent with Suziedelyte (2015)(116)'s findings about the improved problem solving ability, and further indirectly enhanced mathematics knowledge. Furthermore, our research suggest that this cognitive influence could emerge even earlier before school age compared to Suziedelyte (2015)'s sample covering 3-18 years old children.

Limitation of the study includes a high reliance on mother's reports of most covariants, and the extent and direction of any effects are uncertain. In addition, much still needs to be learned about complex parents' reactions and decisions over available resources or external shocks, their own parenting beliefs as well. The dynamic interactions between these inputs and children's own behaviours are still not completely understood.

Ultimately, our research has a clear emphasis on the role of electronic games itself rather than TV or general digital use in early childhood. The games played around the year 2005 generally resemble electronic games played today except for particular massive online multiplayer games and other mobile-based casual games. Nevertheless, these increasingly pervasive new games, together with the advancement of a gaming experience through new technologies (e.g.virtual reality), should be further investigated with the support of more detailed data about digital use. The critical implications of this study help address the increasing public anxieties over digital entertainment that should have not to be deemed as naturally harmful in children's lifeworld. Parents and relevant policies could show more considerations for children's play patterns as playing is an indispensable and essential element at some ages. As we are also likely to see more digital generations of parents, the electronic games could also be a family activity that may receive other benefit via interpersonal interaction.

3.7 Tables and Graphs

Table 3.1: Descriptive Statistics

Variable	Obs	Mean	S.D	Min	Max
Whether plays electronic games	7552	0.69	0.46	0	1
Hours of playing electronic games per weekday (age 5)	7552	0.74	0.99	0	7
Vocabulary (age 3)	7552	51.62	10.52	20	80
Vocabulary (age 5)	7497	56.31	9.94	20	80
Pattern Construction (age 5)	7475	51.55	9.52	20	80
Picture Similarity (age 5)	7487	56.42	9.99	20	80
Total Noncognitive Difficulties (age 3)	7552	8.91	4.93	0	32
Total Noncognitive Difficulties (age 5)	7552	6.70	4.58	0	34
Male	7552	0.48	0.50	0	1
Age (in months)	7552	63.48	2.96	56	75
White	7552	0.91	0.28	0	1
Long-term illness (age 3)	7552	0.16	0.36	0	1
Birth weight (in kilos)	7552	3.38	0.58	0	1
Obesity (age 5)	7552	0.05	0.22	0	1
Days of doing sports per week (age 5)	7552	1.05	1.17	0	6
Hours of watching TV per weekday (age 5)	7552	2.06	1.35	0	7
Siblings	7552	1.26	0.96	0	12
Full-time childcare	7552	0.10	0.29	0	1
Full-time school attendance	7552	0.98	0.15	0	1
Mother's Age (at children's birth)	7552	28.92	5.72	14	51
Mother's BMI (at children's birth)	7552	23.82	4.42	13	59
Mother's Depression	7552	0.36	0.48	0	1
Weekly Family Income	7552	546.03	331.08	20	1698
Urban Area	7552	0.81	0.40	0	1
England	7552	0.63	0.48	0	1
Mother uses a computer at home	7552	0.51	0.50	0	1
Internet Access (at children's birth)	7552	0.47	0.50	0	1
Internet Access (age 5)	7552	0.78	0.41	0	1
Mother's SEC: Managerial and professional	7552	0.25	0.44	0	1
Mother's SEC: Semi-routine or Routine	7552	0.16	0.37	0	1
Mother's SEC: Do not work currently	7552	0.36	0.48	0	1
Father's SEC: Managerial and professional	5680	0.43	0.50	0	1
Father's SEC: Semi-routine or Routine	5680	0.16	0.37	0	1
Father's SEC: Do not work currently	7552	0.07	0.26	0	1
Parent-Children Closeness Scale	7552	33.74	2.14	7	35
Parent-Children Conflict Scale	7552	16.88	5.79	8	40
Parenting: How often read (Age 5) - Everyday	7552	0.55	0.50	0	1
Parenting: How often play active games (Age 5)- Everyday	7552	0.46	0.50	0	1

Note: The sample includes respondents present in all first three waves, from the year 2000 to 2005. A higher value of noncognitive measures (Strengthen and Difficulties Questionnaires) means worse outcomes. A higher value of cognition measures (Vocabulary, Pattern Construction) means better performances. The original income data is in a banded form covering gross earnings, state benefits, and other credit or allowance. This paper used an imputed income variable provided by MCS(63)).

Table 3.2: Effect of Playing Electronic Games on Noncognitive Development: OLS and Poisson Estimation

Outcome	Standardised Total Noncognitive Difficulties								Total Noncognitive Difficulties			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Poisson	NB	GNB
Whether Plays Electronic Games	-0.097***	- 0.117***	-0.066***	-0.064***	-0.068***	-0.068***	-0.065***	-0.064***	-0.293***	-0.286***	-0.285***	-0.291***
	(0.025)	(0.025)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.092)	(0.091)	(0.092)	(0.092)
Male		0.227***	0.087***	0.098***	0.096***	0.089***	0.107***	0.101***	0.462***	0.484***	0.491***	0.490***
		(0.023)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)	(0.085)	(0.087)	(0.088)	(0.087)
Age		-0.018	0.048	0.048	0.058	0.086	0.070	0.072	0.330	0.311	0.267	0.267
		(0.119)	(0.093)	(0.093)	(0.094)	(0.094)	(0.093)	(0.093)	(0.427)	(0.441)	(0.447)	(0.448)
$Age^2/100$		0.008	-0.048	-0.048	-0.055	-0.078	-0.065	-0.067	-0.306	-0.292	-0.261	-0.260
		(0.093)	(0.073)	(0.073)	(0.074)	(0.074)	(0.073)	(0.073)	(0.335)	(0.347)	(0.351)	(0.352)
Past Noncognitive Outcome			0.587***	0.583***	0.567***	0.544***	0.478***	0.472***	0.439***	0.378***	0.413***	0.412***
			(0.011)	(0.011)	(0.011)	(0.012)	(0.014)	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)
Past cognitive outcome			-0.068***	-0.064***	-0.053***	-0.042***	-0.041***	-0.038***	-0.172***	-0.199***	-0.195***	-0.195***
			(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.044)	(0.046)	(0.047)	(0.047)
Birth weight (standardised)				-0.045***	-0.041***	-0.040***	-0.041***	-0.042***	-0.192***	-0.193***	-0.207***	-0.207***
				(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.043)	(0.042)	(0.043)	(0.043)
Mother ever has depression						0.110***	0.093***	0.092***	0.420***	0.406***	0.391***	0.401***
						(0.020)	(0.020)	(0.020)	(0.091)	(0.089)	(0.090)	(0.090)
Mother's SEC: manager and profs						-0.082***	-0.079***	-0.091***	-0.415***	-0.436***	-0.429***	-0.412***
						(0.026)	(0.026)	(0.026)	(0.118)	(0.132)	(0.133)	(0.133)
Household Income (standardised)						-0.017	-0.021*	-0.021*	-0.097*	-0.181***	-0.185***	-0.180***
						(0.011)	(0.011)	(0.011)	(0.051)	(0.061)	(0.061)	(0.061)
Both Parents live in household						-0.095***	-0.096***	-0.096***	-0.440***	-0.325***	-0.357***	-0.363***
						(0.029)	(0.028)	(0.029)	(0.131)	(0.121)	(0.121)	(0.122)
Controls												
Demographic Characteristics		√	√	√	√	√	√	√	√	√	√	√
Health				√	√	√	√	√	√	√	√	√
School/childcare/Other Activities					√	√	√	√	√	√	√	√
Family Background						√	√	√	√	√	√	√
Parent-child Relationship							√	√	√	√	√	√
Parenting Activities								√	√	√	√	√
R^2/ Prosedo R^2	0.002	0.021	0.3749	0.3781	0.3842	0.3940	0.4014	0.4040	0.4040	0.1777	0.0851	0.0849
N	7552	7552	7552	7552	7552	7552	7552	7552	7552	7552	7552	7552

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% The outcome variable is the total noncognitive difficulties that are measured by Strength and Difficulties Questionnaire (SDQ). A negative coefficient means a reduction in total noncognitive problems between age three and five. Demographic controls include gender, ethnicity, country, age (in months), and the number of siblings. Health controls include whether has long-term illness, obesity, and birthweight(standardised). Activities include hours of watching TV and days of sports per week, full-time school and childcare attendance. Family background includes the National Vocational Qualifications (NVQ) and Social Economic Classification (SEC) of the main parent (mother), household weekly income (standardised), urban area, house type (direct ownership, mortgage), and maternal characteristics (BMI, age, and depression at the children's birth, whether drinks everyday). Parenting includes three variables constructed by principal component analysis, which captures parent's involvement (doing indoor/outdoor activities, reading to child, going to library) at age three and five. Also, parent-child relationship scales (standardised) are included. In (12), the generalized binomial model considers age and gender as factors that affect data dispersion.

Table 3.3: Effect of Instrumental Variables on Various Covariates

Covariate	**Mean**	**Mother's PC Use**	**New Internet Access**	**F-test / Chi2-test**
		(s.e)	(s.e)	(p-value)
Whether plays electronic games	0.69	0.086***	0.077***	31.25
		(0.013)	(0.012)	(0.000)
Hours of electronic games per weekday	0.74	0.130***	0.107***	14.79
		(0.026)	(0.026)	(0.000)
Hours of watching TV per weekday	2.06	-0.018	0.002	0.17
		(0.037)	(0.037)	(0.847)
Days of doing sports per week	1.05	0.039	-0.0005	0.99
		(0.030)	(0.029)	(0.370)
Whether has a sleep habit problem	0.25	0.078	0.022	1.48
		(0.065)	(0.063)	(0.477)
Whether reads to children everyday	0.55	-0.022	-0.024	0.25
		(0.056)	(0.055)	(0.884)
Whether has many family rules	0.32	-0.017	0.019	0.31
		(0.060)	(0.058)	(0.859)
Whether has a calm family atmosphere	0.61	0.062	- 0.028	2.05
		(0.059)	(0.057)	(0.358)

Note: *** significant at 1% level; ** at 5% * at 10% . Robust standard errors are in parentheses in the third and fourth columns of estimated coefficients. P-value of F test or Chi-square test is in parentheses in the last column. In the last four rows, logistic regressions were conducted and only raw coefficients are presented in this table to show the potential relationship between the instrumental variables and covariates.

Table 3.4: Effect of Playing Electronic Games on Noncognitive Development: IV and CMP Estimation

Panel A: IV estimates of the impact of gaming					
	(1)	(2)	(3)	(4)	(5)
Method	OLS	IV-2SLS	IV-GMM	IV -LIML	IV-Lewbel
Whether plays electronic games	-0.064***	-0.105	-0.109	- 0.105	-0.023
	(0.020)	(0.224)	(0.256)	(0.224)	(0.057)
First-stage Coefficients:					
Mother uses pc at home		0.086***	0.086***	0.086***	0.087***
		(0.013)	(0.013)	(0.013)	(0.012)
New internet access		0.077***	0.077***	0.077***	0.083***
		(0.012)	(0.012)	(0.012)	(0.012)
Partial R^2		0.009	0.009	0.009	0.069
F-statistic (first stage)		31.25	31.25	31.25	35.53
Kleibergen-Paap Test		61.77	61.77	61.77	562.64
Hansen J-stat		0.178	0.178	0.178	10.70
N	7552	7552	7552	7552	7552

Panel B: IV estimates of the impact of gaming hours					
	(6)	(7)	(8)	(9)	(10)
Method	OLS	IV-GMM	IV -Lewbel	OLS	CMP Ordered Probit
Gaming Hours	-0.011	-0.078	-0.036		
	(0.010)	(0.151)	(0.025)		
Gaming Hours: <1				-0.064***	-0.121
				(0.021)	(0.099)
Gaming Hours : 1- 3				-0.071***	- 0.180
				(0.028)	(0.184)
Gaming Hours : >3				0.007	-0.171
				(0.067)	(0.277)
First-stage Coefficients:					
Mother uses pc at home		0.134***	0.133***		
		(0.026)	(0.027)		
New internet access		0.107***	0.097***		
		(0.026)	(0.026)		
F-statistic (first stage)		14.79	19.28		
N	7552	7552	7552	7552	7552

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% The outcome variable is the standardised total noncognitive difficulties measured by Strength and Difficulties Questionnaire (SDQ). A negative coefficient means a reduction in total noncognitive problems. Whether mother uses pc at home is only reported in the first wave when the children is nine months old. The dummy of new internet access equals to one if the household acquires internet connection after children's birth. All estimations include the same controls as Table 3.2. The parent computer use is only measured at the child's birth (the first wave, the year 2000). The indicator of new internet access equals to one if the family did not have an internet connection at the child's birth but obtained one then. Two-step GMM was implemented in (3) and (7). In Lewbel's IV method (5) and (8), I only chose relatively exogenous variables such as ethnicity, country, urban, mother's birth age to construct heterogeneity-based instruments. The Breusch-Pagan test statistic are 101.62 and 2214 respectively in (5) and (8), suggesting a clear rejection about the null hypothesis of homoskedasticity.

Table 3.5: Effect of Playing Electronic Games on Cognitive Outcomes

Panel A: the Impact on Vocabulary Score						
	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	IV	OLS	IV	OLS	CMP
Whether plays electronic games	0.022	0.408*				
	(0.021)	(0.243)				
Gaming Hours			-0.008	0.547*		
			(0.010)	(0.312)		
Gaming Hours: <1					0.036	0.191**
					(0.023)	(0.091)
Gaming Hours : 1- 3					-0.006	0.277
					(0.029)	(0.169)
Gaming Hours : >3					-0.060	0.342
					(0.067)	(0.256)
F-statistic (first stage)		30.38		13.54		
N	7497	7497	7497	7497	7497	7497
Panel B: the Impact on Pattern Construction						
	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	IV	OLS	IV	OLS	CMP
Whether plays electronic games	0.111***	0.525*				
	(0.024)	(0.273)				
Gaming Hours			0.023*	0.386*		
			(0.013)	(0.204)		
Gaming Hours: <1					0.114***	0.273***
					(0.026)	(0.094)
Gaming Hours : 1- 3					0.108***	0.406**
					(0.033)	(0.174)
Gaming Hours : >3					0.052	0.473*
					(0.075)	(0.264)
F-statistic (first stage)		30.12		13.62		
N	7475	7475	7475	7475	7475	7475
Panel C: the Impact on Picture Similarity						
	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	IV	OLS	IV	OLS	CMP
Whether plays electronic games	0.078***	0.523*				
	(0.025)	(0.274)				
Gaming Hours			0.020	0.453*		
			(0.013)	(0.235)		
Gaming Hours: <1					0.085***	0.262**
					(0.026)	(0.108)
Gaming Hours : 1- 3					0.057*	0.391**
					(0.033)	(0.199)
Gaming Hours : >3					0.109	0.586*
					(0.077)	(0.302)
F-statistic (first stage)		30.02		13.32		
N	7487	7487	7487	7487	7487	7487

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% .The outcome variables are standardised score. Two-step GMM is applied in IV estimation. The first-stage of CMP process is an ordered-probit model with a significant cut-off at three hours.

Table 3.6: Heterogeneity in the Effect of Playing Electronic Games by Gender

Panel A: Descriptive Statistics	**Boys**		**Girls**	**t-diff**
Whether plays electronic games	73%		65%	0.08***
Average Gaming Hours (per weekday)	0.88		0.62	0.26***
Average TV Hours (per weekday)	2.12		1.99	0.13***
Average Sports Days (per week)	0.94		1.15	- 0.21***
Average Total Noncognitive Difficulty score	7.21		6.22	0.99***
Average Vocabulary Score	56.09		56.52	-0.23*
Average Picture Similarity Score	55.82		56.99	- 1.17***
Average Pattern Construction Score	50.95		52.11	- 1.15***

Panel B: OLS and IV estimates	**Boys**		**Girls**	
Method	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties				
Whether plays electronic games	-0.076**	-0.154	-0.058**	-0.050
	(0.032)	(0.354)	(0.026)	(0.280)
F-statistic (first stage)		14.83		17.30
N	3638	3638	3914	3914
Outcome: Pattern Construction				
Whether plays electronic games	0.114***	0.423	0.107***	0.654*
	(0.037)	(0.429)	(0.031)	(0.351)
F-statistic (first-stage)		14.39		16.71
N	3592	3592	3883	3883
Outcome: Vocabulary				
Whether plays electronic games	0.014	0.598	0.028	0.398
	(0.033)	(0.528)	(0.028)	(0.369)
F-statistic (first stage)		14.74		12.61
N	3604	3604	3893	3893
Outcome: Picture Similarity				
Whether plays electronic games	0.098***	0.505	0.066**	0.731*
	(0.037)	(0.422)	(0.033)	(0.417)
F-statistic (first stage)		14.53		16.40
N	3602	3602	3885	3885

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% . All outcome variables are standardised.

Table 3.7: Heterogeneity in the Effect of Playing Electronic Games by Family Background

Panel A: Subsamples by Family Income Quantiles	**Lowest 25%**		**25% -50%**		**50% - 75%**		**Above 75%**	
Description								
Whether plays electronic games (%)	66%		51%		71%		68%	
Whether mother uses pc at home (%)	31%		42%		57%		73%	
Whether obtains new internet access (%)	36%		41%		35%		24%	
Average Total Noncognitive Difficulties	8.2		7.1		6.2		5.25	
Average Pattern Construction Score	49		51		52		53	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties								
Whether plays electronic games	- 0.063	0.030	-0.124***	-0.078	-0.058	-0.048	-0.002	-0.510
	(0.045)	(0.446)	(0.043)	(0.558)	(0.040)	(0.375)	(0.033)	(0.417)
F-statistic (first stage)		10.29		5.03		8.75		6.87
N	1888	1888	1888	1888	1888	1888	1888	1888
Outcome: Pattern Construction								
Whether plays electronic games	0.112**	- 0.034	0.116**	1.06	0.118***	0.461	0.110**	0.892
	(0.047)	(0.047)	(0.050)	(0.738)	(0.047)	(0.500)	(0.046)	(0.586)
F-statistic (first stage)		9.74		4.80		8.73		6.70
N	1855	1855	1873	1873	1872	1872	1875	1875

Panel B: Subsamples by Mother's NVQ	**Level 1 or Other**		**Level 2**		**Level 3**		**Level 4 or 5**	
Description								
Whether plays electronic games (%)	70%		70%		70%		68%	
Whether mother uses pc at home (%)	26%		41%		47%		68%	
Whether obtains internet access (%)	40%		39%		37%		27%	
Average Total Noncognitive Difficulties	8.41		7.1		6.7		5.7	
Average Pattern Construction Score	49		51		51		53	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties								
Whether plays electronic games	-0.167***	-0.111	-0.061	0.642	-0.043	-0.555	-0.035	-0.864*
	(0.064)	(0.458)	(0.042)	(0.495)	(0.049)	(0.590)	(0.027)	(0.485)
F-statistic (first stage)		10.02		8.19		9.19		6.87
N	1137	1137	2119	2119	1251	1251	3045	3045
Outcome: Pattern Construction								
Whether plays electronic games	0.231***	0.874	0.124***	-0.031	0.132**	-0.096	0.066*	1.360**
	(0.067)	(0.564)	(0.045)	(0.534)	(0.062)	(0.469)	(0.035)	(0.625)
F-statistic (first stage)		9.4		7.71		9.88		6.92
N	1118	1118	2101	2101	1237	1237	3019	3019

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10%. All outcome variables are standardised. Rough equivalents to NVQ 1-5 Levels are : GSCE (grade D-G), GCSE (grades A* - C), A/AS levels, Higher Education Certificate, Higher Education Diploma/Degree respectively. In this table, the first NVQ group also includes the people with entry-level qualifications.

Table 3.8: Heterogeneity in the Effect of Playing Electronic Games by Cognitive and Noncognitive Level

Panel A: Classifications of Noncognitive Level	**Normal to average**		**Slightly raised**		**Abnormal**	
Method	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties						
Whether plays electronic games	- 0.063***	-0.194	-0.085	- 0.023	- 0.017	- 0.880
	(0.020)	(0.241)	(0.080)	(0.455)	(0.104)	(1.526)
F-statistic (first stage)		22.89		9.28		1.33
N	6261	6261	703	703	588	588
Outcome: Pattern Construction						
Whether plays electronic games	0.108***	0.483	0.083	-0.047	0.217***	2.940
	(0.025)	(0.316)	(0.086)	(0.522)	(0.100)	(2.867)
F-statistic(first stage)		22.45		8.87		0.81
N	6214	6214	691	691	570	570

Panel B: Quantiles of Vocabulary Score						
	Lower 25%		**25% - 75%**		**Top 25%**	
Method	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties						
Whether plays electronic games	-0.132***	-0.192	-0.058**	0.104	0.014	-0.310
	(0.043)	(0.462)	(0.027)	(0.286)	(0.041)	(0.517)
F-statistic(first stage)		9.44		17.71		5.31
N	2109	2109	3954	3954	1489	1489
Outcome: Pattern Construction						
Whether plays electronic games	0.040	-0.095	0.128***	0.612	0.186***	1.021
	(0.047)	(0.501)	(0.032)	(0.384)	(0.052)	(0.622)
F-statistic(first stage)		8.79		16.97		5.79
N	2074	2074	3916	3916	1485	1485

Note: Robust standard errors in parentheses. *** significant at 1% level; ** at 5% * at 10%. For the non-cognitive level, a SDQ score in a range of 0 to 13 is classified as a normal average; a range of 14 to 16 is slightly above average; a score higher than 17 is defined as high and abnormal.

Table 3.9: Robustness Check: OLS and IV estimates in Alternative Samples

Panel A: Subsamples by Family Background	**Maternal Health** (no depression & good health)		**Maternal Age** (>=25)		**Has TV rules**		**Parenting Competence** (above average)	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties								
Whether plays electronic games	-0.035	0.128	-0.079***	-0.157	-0.050*	-0.195	-0.033	0.114
	(0.024)	(0.262)	(0.022)	(0.236)	(0.028)	(0.44)	(0.024)	(0.263)
F-statistic (first stage)		17.09		26.01		7.82		19.33
N	4427	4427	5828	5828	3745	3745	4634	4634
Outcome: Pattern Construction								
Whether plays electronic games	0.100***	0.249	0.114***	0.694**	0.123***	0.325	0.110***	0.237
	(0.030)	(0.337)	(0.027)	(0.308)	(0.034)	(0.542)	(0.031)	(0.331)
F-statistic (first stage)		17.00		24.95		7.05		19.79
N	4395	4395	5779	5779	3711	3711	4592	4592

Panel B: Subsamples by Individual Characteristics	**Health Problem** (obesity or other illness)		**TV in own room**		**Watching TV** (1-3 hours)		**Doing Sports** (>1 day per week)	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties								
Whether plays electronic games	-0.060	0.049	-0.053	0.232	-0.060***	-0.062	-0.078***	-0.228
	(0.048)	(0.610)	(0.033)	(0.447)	(0.025)	(0.269)	(0.025)	(0.367)
F-statistic (first stage)		5.21		9.80		20.49		9.88
N	1693	1693	3505	3505	4917	4917	4438	4438
Outcome: Pattern Construction								
Whether plays electronic games	0.107**	0.232	0.101***	0.565	0.143***	0.488	0.131***	0.944**
	(0.050)	(0.703)	(0.037)	(0.516)	(0.029)	(0.320)	(0.030)	(0.480)
F-statistic (first stage)		4.91		9.26		19.79		9.86
N	1669	1669	3464	3464	4867	4867	4408	4408

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% . All outcome variables are standardised. The indicator of health problem equals to one if the children has obesity, long-term illness or any other illness that limits daily activities. The indicator of having a TV in children's own room is measured at age 11 in the fourth wave (the year 2007).

Table 3.10: Robustness Check: Model Specifications and Alternative Controls

Panel A: Alternative Specification								
	CT		**FD**		**FD** (with controls for past performance)		**Percentage Change**	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties								
Whether plays electronic games	-0.086***	-0.321	0.039	-0.131	0.069***	0.117	8.05**	-10.32
	(0.022)	(0.246)	(0.025)	(0.278)	(0.022)	(0.241	(3.65)	(38.15)
F-statistic (first stage)		31.61		31.61		31.25		31.46
N	7552	7552	7552	7552	7552	7552	7313	7313
Outcome: Vocabulary								
Whether plays electronic games	0.024	0.656**	0.023	0.066	0.022	0.394*	0.415	3.39
	(0.023)	(0.270)	(0.025)	(0.274)	(0.021)	(0.234)	(0.581)	(6.49)
F-statistic (first stage)		30.72		30.72		30.38		30.72
N	7497	7497	7497	7497	7497	7497	7497	7497

Panel B: Alternative Controls								
	Including parenting style		**Including parenting competence**		**Including father's parenting**		**Lasso-selected**	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Outcome: Total Noncognitive Difficulties								
Whether plays electronic games	-0.063***	-0.113	- 0.060***	-0.147	-0.071***	-0.287	-0.063***	-0.115
	(0.020)	(0.222)	(0.020)	(0.220)	(0.023)	(0.297)	(0.020)	(0.224)
F-statistic (first stage)		31.97		31.52		15.64		30.50
N	7552	7552	7552	7552	5103	5103	7552	7552
Outcome: Pattern Construction								
Whether plays electronic games	0.112***	0.516*	0.112***	0.515*	0.147***	0.535	0.109***	0.555**
	(0.024)	(0.270)	(0.024)	(0.272)	(0.029)	(0.382)	(0.024)	(0.277)
F-statistic (first stage)		30.83		30.37		14.87		29.33
N	7475	7475	7475	7475	5057	5057	7475	7475

Note: Robust standard errors are in parentheses. *** significant at 1% level; ** at 5% * at 10% . In panel A, "CT" is a contemporary relationship specification that does not include any past cognitive and noncognitive outcomes as controls. "FD" is the first-difference specification that uses $Y_{t-1} - Y_t$ as the outcome variable for noncognitive difficulties to better reflect the improvement. And this measure is the reverse for the cognitve test. "Percentage change" refers to the specification that uses the $100 * (Y_{t-1} - Y_t)/Y_{t-1}$ as the outcome variable for noncognitive difficulties. It is $100 * (Y_t - Y_{t-1})/Y_{t-1}$ for the cognitive test. In panel B, Post-Double-Selection (PDS) LASSO (Belloni *et al.*, 2014)(14) was applied in selecting controls.

Figure 3.1: Total Noncognitive Difficulties (age five)

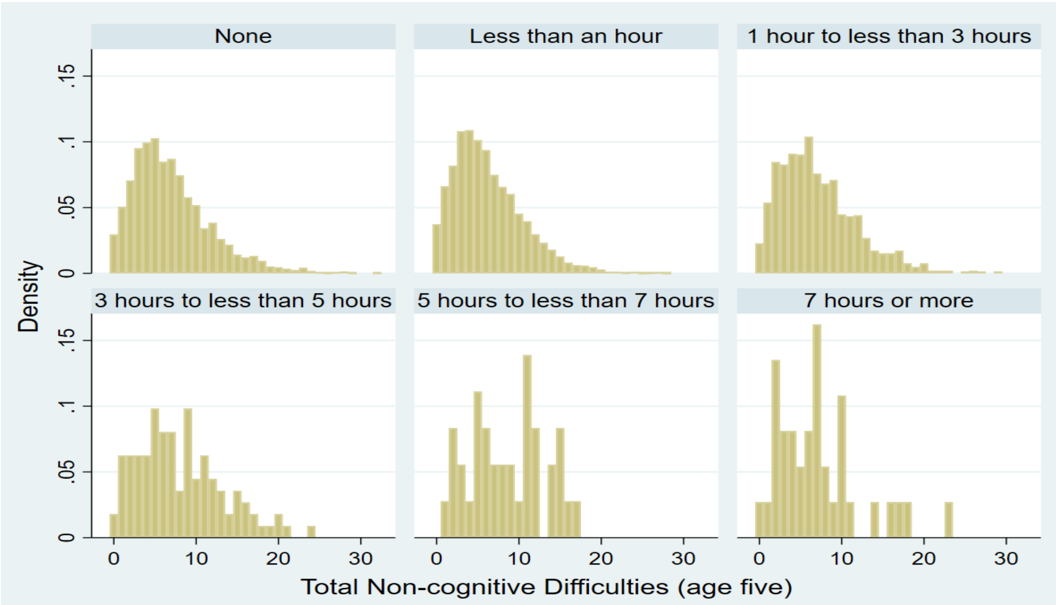


Figure 3.2: Pattern Construction Score (age five)

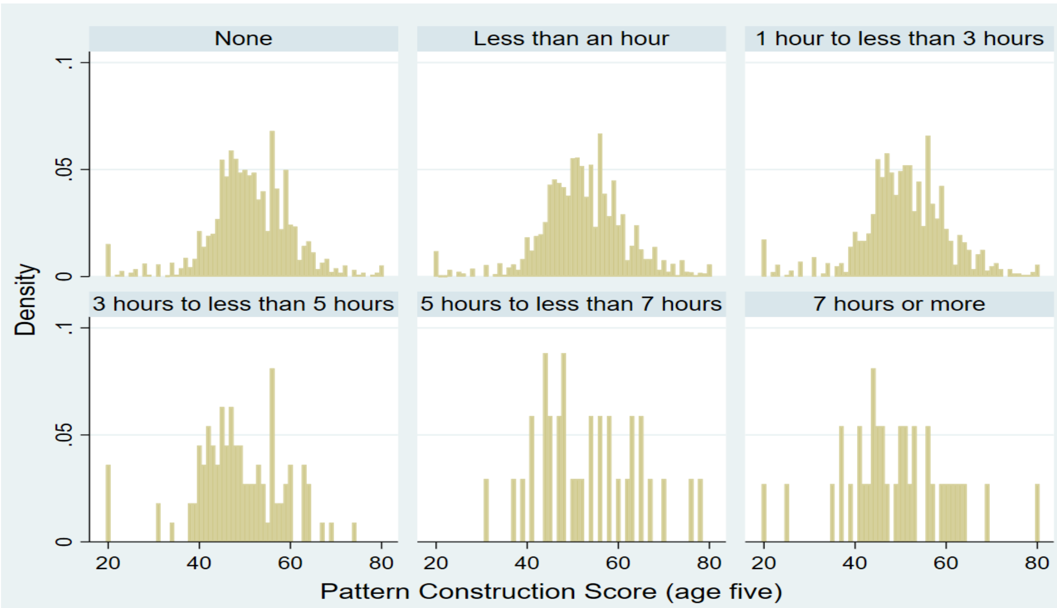
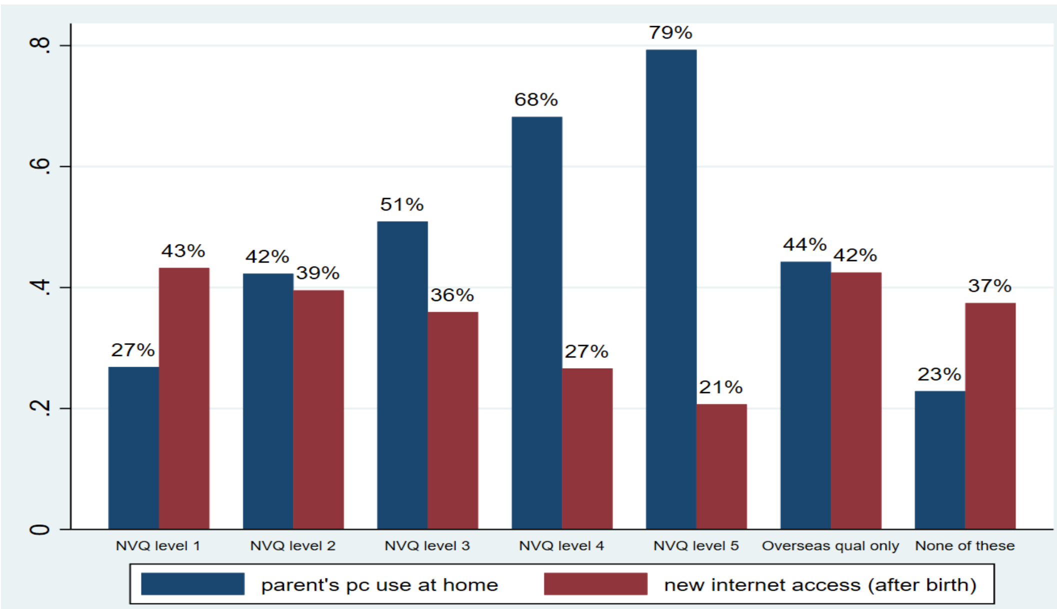


Figure 3.3: Parent's PC Use and Home Internet Access (age five)



3.8 Appendix

Sub scales of Strength and Difficulties Questionnaires (SDQ)

1. **Emotional Symptoms Scale**
    - Often complains of headaches/stomach aches/sickness
    - Often seems worried
    - Often unhappy
    - Nervous or clingy in new situations
    - Many fears, easily scared
2. **Conduct Problem**
    - Often has temper tantrums or hot tempers
    - Generally obedient*
    - Often fights with other children
    - Often lies or cheats
    - Steals from home, school or elsewhere
3. **Hyperactivity Scale**
    - Restless, overactive
    - Constantly fidgeting or squirming
    - Easily distracted, concentration wanders
    - Thinks things out before acting*
    - Sees tasks through to the end*
4. **Peer Problems**
    - Rather solitary, tends to play alone
    - Has at least one good friend*
    - Generally liked by other children*

- Picked on or bullied
- Gets on better with adults than with other children

5. **Pro-social Scale**

   - Considerate of other people's feelings
   - Shares readily with other children
   - Generally liked by other children
   - Helpful if someone is hurt
   - Kind to younger children

* denotes items that are reversed in generating sub scales on behaviour problems
For different levels of SDQ score (parent completed version):
0 - 13: Normal average;
14 - 16: Slightly above average;
17 - 40: High and abnormal.

Table 3.11: IV Estimation: First-stage Coefficients

Outcome: Whether plays electronic games			
	Grouped	**Boys**	**Girls**
	(1)	(2)	(3)
Method	OLS	OLS	OLS
Mother uses pc at home	0.086***	0.076***	0.097***
	(0.013)	(0.017)	(0.018)
Internet Access	0.077***	0.078***	0.077***
	(0.012)	(0.017)	(0.018)
Male	0.085***		
	(0.011)		
Age	0.068	0.126	0.018
	(0.059)	(0.082)	(0.083)
White	-0.151**	-0.208***	-0.122
	(0.063)	(0.077)	(0.095)
Past noncognitive difficulties	-0.016**	-0.028***	-0.005
	(0.007)	(0.010)	(0.010)
Past cognitive score (vocabulary)	-0.001	-0.004	0.002
	(0.006)	(0.008)	(0.008)
Urban	0.052***	0.056***	0.044**
	(0.014)	(0.020)	(0.021)
Birth weight (standardised)	0.009*	0.011	0.008
	(0.005)	(0.008)	(0.008)
Mother's age at child's birth	0.002*	0.001	0.003*
	(0.001)	(0.002)	(0.002)
Depression (mother)	0.017	0.026*	0.012
	(0.011)	(0.016)	(0.016)
SEC: manager and profs (mother)	0.036**	0.036	0.031
	(0.016)	(0.023)	(0.023)
Household weekly income (standardised)	-0.012*	-0.002	-0.020**
	(0.007)	(0.010)	(0.010)
Both parents live in household	0.047***	0.059***	0.035
	(0.016)	(0.022)	(0.023)
Full-time childcare Attendance	-0.034*	0.029	-0.091***
	(0.019)	(0.025)	(0.027)
N	7552	3638	3914

Note: Robust standard errors in parentheses. *** significant at 1% level; ** at 5% * at 10% . The table only presents some selected covariates of interest in predicting children's game playing. The first-stage estimation includes the same control covariates as those in main regressions.

Table 3.12: Principal Component Analysis of Parenting Variables

Parenting Activities	Component 1	Component 2	Component 3
Read to child (age 3)	-0.0999	**0.6035**	-0.0355
Read to child (age 5)	0.0547	**0.5486**	0.1817
Help with drawing (age 3)	**0.3669**	0.0960	-0.1827
Help with drawing (age 5)	0.0004	0.1358	**0.5363**
Help with counting (age 3)	**0.6589**	-0.0032	0.0114
Help with alphabet (age 3)	**0.6409**	-0.0350	0.0381
Play indoor activities (age 5)	0.0732	-0.0550	**0.5252**
Play musical activities (age 5)	-0.0200	-0.0579	**0.5928**
Take children to library (age 5)	0.0410	**0.5473**	-0.1260

Table 3.13: Effect of Playing Electronic Games on the Subcategories of Noncognitive Difficulties

Panel A: Grouped	***Internalizing Problem***						***Externalizing Problem***							
	Emotion		Peer		Total		Conduct		Inattention		Total		Procosial	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Whether plays electronic games	-0.076***	-0.209	-0.042*	-0.005	-0.073***	-0.143	-0.032	- 0.235	-0.033	0.032	-0.039*	-0.046	0.016	0.001
	(0.023)	(0.259)	(0.023)	(0.254)	(0.024)	(0.257)	(0.021)	(0.242)	(0.020)	(0.223)	(0.020)	(0.227)	(0.022)	(0.239)
F-statistic (first stage)		31.25		31.26		31.25		31.29		31.29		31.26		31.83
N	7552	7552	7552	7552	7552	7552	7552	7552	7552	7552	7552	7552	7526	7526
Panel B: Boys														
Whether plays electronic games	-0.050	-0.067	-0.080**	-0.221	-0.074**	0.017	-0.013	-0.257	-0.055*	0.054	-0.056*	-0.230	0.031	-0.392
	(0.035)	(0.393)	(0.036)	(0.424)	(0.037)	(0.403)	(0.033)	(0.427)	(0.032)	(0.366)	(0.032)	(0.365)	(0.036)	(0.390)
F-statistic (first stage)		14.89		14.79		14.83		14.91		14.49		14.83		15.21
N	3638	3638	3638	3638	3638	3638	3638	3638	3638	3638	3638	3638	3621	3621
Panel C: Girls														
Whether plays electronic games	-0.094***	-0.288	-0.013	0.187	-0.072**	-0.226	-0.052*	-0.205	-0.023	0.001	-0.031	0.091	0.007	0.340
	(0.031)	(0.350)	(0.030)	(0.337)	(0.031)	(0.324)	(0.028)	(0.301)	(0.026)	(0.275)	(0.026)	(0.279)	(0.028)	(0.299)
F-statistic (first stage)		17.21		17.27		17.30		17.20		16.87		17.30		17.36
N	3914	3914	3914	3914	3914	3914	3914	3914	3914	3914	3914	3914	3905	3905

Note: Robust standard errors in parentheses. *** significant at 1% level; ** at 5% * at 10% .

Notes

[1]By comparison, the American Academy of Paediatrics (AAP) in the U.S. recommends no screen time at all for children under the age of 18 months, and a maximum of one hour a day up to the age of five.

[2]Although their empirical analysis fail to reveal any statistical significance in predicting children's computer attitudes or usage, such results are vulnerable to a small sample and omitted bias. The insignificant relationship might be explained by the age of sampled children who are usually more than ten years old: their ICT usage are likely affected more by peers and school life than the parents. In contrast, parents and family environment appear to play important roles in ICT usage among young children before a school age.

[3]The primary loss of our observations comes from the inclusion of parenting behaviours - reducing the sample size by around 3,000. Overall, our working sample is relatively more advantaged than the group with missing information about parenting activities. After imputation of missing data on these parenting variables, I obtain similar estimates from a larger sample of 9458 observations.

[4]There are three different scores in MCS test: the Raw, the Ability and T-Scores. Raw scores are simply the number of items the cohort member child answered correctly and do not take into account the answering time or age. The ability scores are a transformation of the raw scores that only take into account of the specific item set administered. T-scores are adjusted for children's age group (of three months)and for the mean scores of the BAS norming group. More information could be referred to the work by Elliot *et al.,*(1996, (41)1997(42)).

[5]source: www.vgchartz.com.

[6]Due to the low response rate of fathers, I do not control much for father's SEC and NVQ in main regressions but present relevant results in the section of robustness check.

[7]CPRS is a 15-item self-report instrument to describe the stabliilty and consistency of parents' perception of their relationships with their children. It is suggested that maternal and paternal ratings of closeness and conflict were somewhat stable across the preschool period and play important role in developing interpersonal relationship and academic performance during the early school years. (see work by Pianta *et al.,*(1992(97), 2011(38))

[8]A total SDQ score (parent's report base) higher than 17 is classified as the "abnormal" category. A range between 14 to 16 is suggested as "slightly raised". See Goodman 2000(58) for detailed information.

[9]The robustness of Lewbel's method to choices of variables was examined. Results from other sets of variables were generally consistent in sign and magnitude with those in Table 3.4, between - 0.020 to - 0.040. In Table 3.4, a parsimonious variable set is chosen for its larger improvement in first-stage regression.

[10]The gender gap in educational outcomes is widely discussed. But it is less clear how early the gender gap emerges. Some researches show that girls consistently score higher in many aspects of noncognitive development, especially the social competence (e.g. DiPrete *et al.,*2012(35); Cornwell *et al.,*2013(25)).

Chapter 4

Internet Use and Cognitive Decline Among Retirees

4.1 Introduction

The use of Information and Communication Technology (ICT) has increasingly become mainstream in society. Naturally, this has led to widespread discussion about the impact of ICT on people's lives. Much of the discussion has focused on the impact of technology on children and teenagers; less attention has been paid to the interaction of the elderly with digital technologies. Given that the share of older people in the population of developed countries will continue to grow rapidly, it is worth understanding the benefits or costs of technology use among older people.

This study aims to identify the causal relationship of ICT usage on the cognitive function of older people. Potentially, there are many benefits from ICT usage such as facilitation of routine tasks, information accessing, entertainment, social connection and mental stimulation, all of which have the potential to improve life quality (Czaja *et al.*,1993(29), 2001(30); Jones and Bayen 1998(71); McConatha *et al.*,1994(88)). This has motivated a series of experimental studies, primarily in psychology, that have aimed to assess the impact of computer skills and internet use on various outcomes such as loneliness, depression, physical functioning, and general life satisfaction (White *et al.,*2002(122); Shapira *et al.*, 2007(108); Sleger *et al.*,2008(112), 2009(111)). These studies typically have found no relationship between measures of computer competency and computer use, and these wellbeing outcomes. A shortcoming of this research is a lack of pre-test controls for personal characteristics that are likely to play an important role in the ICT usage of older people in many experimental settings (McConatha *et al.*,1994(88); Sleger *et al.*,2008(112)). At the same time, the nature of these studies, which often use convenience samples drawn from, for instance, older people living in community dwellings (Elliot *et al.*, 2013(40)) or in nursing homes (White *et al.*,2002(122); Shapira *et al.*,2007(108)), raise concerns regarding external validity.

Another body of recent research uses larger cross-sectional datasets to examine the effect of ICT use on important life outcomes of older people. This literature finds mixed results. For instance, Lelkes *et al.*(2013)(76) use the European Social Survey and report a statistically significantly positive association between regular internet usage and life satisfaction after controlling for many personal characteristics. A similar relationship is also found using US datasets such as Health and Retirement Study(HRS) and the Midlife in the United States (MIDUS)(Tun and Lachman 2012(119); Heo *et al.*,2015(67)). On the other hand, Elliot *et al.*(2013)(40) examined the National Health and Aging Trends Study, and using structural equation modelling, found no direct relationship between ICT usage and mental health.

Relatively few studies have focused on the impact of ICT use on the cognitive function of older people. It is widely discussed that computer-based activities influence many aspects of cognition such as attention, memory, spatial abilities and problem solving (see Rogers *et al.*,2005(100)). Again, the evidence of this point is mixed. Earlier studies and surveys showed a positive impact of computer-based interventions on cognitive ability (McConatha *et al.*,1994(88)). However, Sleger *et al.*(2009)(111), again in a small scale experimental setting, find an insignificant impact of a fortnight training program and subsequent computer use on cognitive function. In contrast, evidence from larger samples suggests a positive association between computer use and cognition across adulthood generally, conditioning on many controls for personal characteristics (Tun and Lachman 2012(119); Sleger *et al.*,2012(113)). Overall, although there is a widespread belief in the benefits of using ICT among older people, the current literature reports inconsistent results that vary by sample designs and composition.

The critical challenge in identifying the impact of ICT use is the endogenous nature of ICT use. The incidence and frequency of ICT usage amongst older people reflect a range of factors that, themselves, are likely to be related to cognitive function. In the absence of an empirical strategy to address this, it is difficult to causally interpret statistical associations between ICT use and cognitive function. There are many potential threats to this interpretation, including for instance the potential for cognitive function to influence the utility individuals received from ICT use and omitted or inaccurately measured factors such as wealth and income that are likely to influence both cognitive function and ICT use[1] .

We return to this issue and focus on the impact of ICT usage on the rate of decline of cognitive function among retirees. We do this using a large multi-country longitudinal dataset, the Survey of Health, Ageing and Retirement in Europe (SHARE) and focus on one particularly salient form of ICT usage, internet use. We focus on a specific sample, those who have retired since 2004. This has two advantages: first it reduces the interconnections between computer use, retirement decisions and cognitive development (Friedberg 2003(55); Banks *et al.*, 2010(11); Bonsang *et al.*, 2012(16); Mazzonna and Peracchi 2012(87)). Second, this group of individuals entered the workforce and embarked on careers in the period before the general introduction of workplace computers that occurred in the 1980s. This motivates an instrumental variable approach, where we rely on differential rates of within occupation computerisation that occurred during these individual's working lives but are unlikely to be a feature of their original occupational choice. We use this within career variation in computer intensity to provide plausibly exogenous variation in the likelihood of computer use after retirement. This, in practice, proves to be a highly relevant instrument and in the results section, we investigate the robustness of our results to potential violations in the exclusion restriction. We demonstrate that current internet use leads to marked reductions in the rate of decline of cognitive function amongst retirees. This effect survives a range of approaches aimed at examining robustness.

The remainder of this chapter unfolds as follows: in section two and three, we describe the data and identification method. Section four presents the results of linear and instrument estimations. What follows are a few robustness checks. Finally, we summarise and discuss our findings.

4.2 Data

Our data is drawn from the Survey of Health, Ageing and Retirement in Europe (SHARE), a large longitudinal pan-European study that collects information about health, household, employment history, and social-economic status of older people in European countries[2]. The interviews were carried out every other year and currently SHARE provides six waves spanning from 2004 to 2015. All data are collected by face-to-face, computer-aided personal interviews, supplemented by a self-completion paper and pencil questionnaire. People who are over age fifty and speak the official language of each country are eligible for the study. People who live abroad or in hospital, or has moved out during survey period are dropped out by SHARE. Thus, our sample contains all people born in 1954 or earlier in the first wave.

4.2.1 Sample Selection

We restrict our sample to those survey respondents who participated in the first (2004), fourth (2011), and fifth (2013) waves of interviews because only those waves collected the information necessary for our analysis. The first wave contains detailed information about the occupations of respondents which is used for our instrumental variable identification. In the fourth and fifth waves, respondents were asked about current internet usage, computer skills, computer (or a tablet) usage at their current job or the last job before their retirement.

The upper panel in Table 4.1 illustrates our sample selection and data attrition. 30,434 age-eligible people were interviewed at the beginning year 2004, and the retention rate is around 70% across each two waves. Starting from wave two, only one age-eligible person per household and their spouse or partner regardless of age were interviewed. Therefore, only around 20,000 people from the baseline sample were interviewed in following surveys. Until the year 2015, we have 9,902 people participated all first, fourth and fifth waves. The traceable mortality[3] rate across waves are approximately 4%. There are 3,228 cases of decease between the year 2004 and 2015, around 10.6% of the original sample.

Near half claimed retirement status and around 8% people never worked. In particular, we restrict our sample to those who have reported retiring before the year 2004 and have not done any other paid job in the last four weeks. And this status is consistent in all three waves. Thus, we excludes people who may rejoin workforce between the year 2004 and 2013, and those declare themselves as retired simply because they left their career job. These further restrictions leaves 3,924 respondents for our analysis.

The lower panel in Table 4.1 presents a comparison between our working sample and the remaining participants who also participated in the same waves. Essentially, our restricted sample is drawn from older cohorts and reflect more clearly a group of retirees. In total, there were 3,798 observations in our working sample at an average age of 77 from ten European countries. They were, on average, born in the year 1936 and retired approximately 60 on average. They started their final job in the late 1960s and retired in the year 1995 on average. Around 25% of respondents live in a big city or the suburbs of a city. The average schooling year is 9.7. Around 60% are married and are living with their spouse.

4.2.2 Main Variables

Our outcome of interest is the respondent's cognitive function. In each regular wave of SHARE, the cognitive function of the respondents was measured. To capture different aspects of cognitive function, there are a range of measures such as orientation, vocabulary, numeracy and verbal memory etc. In this paper, we focus on the word recall test in which respondents are told a list of ten words and are then asked to recall them immediately as well as after a delay of five minutes. The verbal memory is particularly susceptible to age-related declines in cognitive performance. Such memory test is suggested as an effective tool in early screening tests for dementias that commonly impair recent memory (Knopman 1989)(74). Moreover, this measure helps reduce the potential ceiling effect that may appear in the verbal fluency (such as naming animals) as people from different countries or occupations may have very different perception about the group of the word to be named (Bonsang *et al.*,2012(16)). As shown in Figure 4.1, the number of successfully recalled words declines with age, and women can recall more words. The exception is the first group which contains 197 people who actually retired before a national statutory age in the year 2004, possibly as a result of negative shocks.

The aim of our study is to examine how ICT usage among older people affects their cognitive function. In Table 4.1, we can see that around 27% of people reported internet usage during the past seven days. It is less likely that the internet use is by using a smartphone or other mobile device: nearly 70% of older people in the UK report using a desktop or laptop computer as their device to access the internet (Matthews and Nazroo, 2015(86)). In Figure 4.2, we can see that generally, the proportion of internet users decreases with age, cognitive function, and years since retirement. We can also see that the proportion of those who used a computer in their final job before retirement increases across the distribution of cognitive function, and ICT usage decreases with age and retired years.

4.2.3 Country Heterogeneity

SHARE is designed to be cross-nationally comparable and its baseline survey includes eleven European countries: Austria, Belgium, Netherlands, Germany, France, Switzerland, Italy, Spain, Denmark, Sweden and Greece. Greece is not included in our sample because of its missing in the fourth and fifth waves. Table 4.2 presents variations between countries based on our working sample.

The average score in the delayed work recall is around 2.3 for Mediterranean countries (Italy and Spain), near one fewer word recalled compared to other countries. Differences between Scandinavian countries (Sweden and Denmark) and Central Europe (Austria, Belgium, Netherlands, Germany, France and Switzerland) is less marked.

Regarding ICT use, our figure indicates that no more than 10% people report recent internet use in Spain and Italy, but the figure is over 40% in Netherlands and Denmark. According to the ICT development index[4] in 2015, Denmark, Sweden, Switzerland and Netherlands ranked within top ten through international comparisons. Belgium, Austria, France, Spain and Italy ranked after 20. Moreover, individual-level factors such as education, wealth, health, social networking, prior ICT experience, often suggested as important drivers of ICT use, differ greatly by European countries.

Labour force aspects are more complex in terms of pension systems, welfare schemes and labour market policies across countries. In general, Nordic countries have a high employment participation and continuity for both sexes. There is a high proportion of people identified as never worked in Italy and Spain, especially among females.

4.3 Identification Method

Our main empirical approach follows a value-added education production function specification:

$$Y_{it} = \alpha_0 + \alpha_1 Y_{it-1} + \gamma Internet_{it} + \alpha_2 X_{it} + \epsilon_{it} \quad (4.1)$$

Where Y_{it} is cognitive function measured at time t (the year 2013) for individual i. In the fourth and fifth waves of SHARE, individuals were tested in word recall (immediate and delayed), numeracy, and orientation. The lagged outcome controls for initial cognitive function level that we assume declines with age at a rate of α_1. We focus mainly on the raw score and the standardised score of the delayed recall test rather than a log transformation because 831 observations with zero recalled words would be lost under a log transformation in our working sample of 3798 observations. In further checks, we examine the robustness of our results to alternative measures. $Internet_{it}$ is a dummy variable indicating whether an individual used the internet at least once during the past seven days for e-mailing, searching for information, making purchases, or for any other purpose. γ is the parameter of interest. X_{it} contains individual-level control variables. These are demographic characteristics (gender, age, country of survey), years since retirement, years of schooling, health (Body Mass Index, whether drinks more than two glasses every day, the number of visits to a doctor, whether has chronic diseases, physical inability), and household conditions (residence in urban or rural area, house ownership, household size, whether in a nursing house, marital status, annual household income[5]).

Non-random variation in internet access and usage presents barriers to interpreting γ as causal. One concern is selection into internet usage based on unobservable factors influencing the rate of cognitive decline. For instance, people with a lower rate of cognitive decline may confront less cognitive challenges in using a computer or internet. There could also be a positive feedback between internet use and cognitive function. This endogeneity motivates an instrumental variable strategy aimed at utilizing plausibly exogenous variation in internet use. Our main strategy is to rely upon non-uniform computerisation of occupations that occurred from the 1980s[6] onwards as documented in a large literature (Autor *et al.*,1998(8),2003(9),2015(31).). On average, our sample was born in 1935 and began working before the spread of personal computer in workplaces after the 1980s. Hence, they are less likely to have made decisions about careers after expectations of computerisation could reasonably have been formed. This, we argue, leads to work-life exposure to computers likely to affect post-retirement computer usage but unlikely to be driven by selection.

Our instrumental variable strategy is to estimate the following set of equations:

$$Y_{it} = \alpha_0 + \alpha_1 Y_{it-1} + \gamma Internet_{it} + \alpha_2 X_{it} + \epsilon_{it} \ (4.2)$$
$$Internet_{it} = \beta_0 + \beta_1 Y_{it-1} + \theta Exposure_i + \beta_2 X_{it} + \mu_{it} \ (4.3)$$

It is important to note that the exclusion restriction of our two-stage estimation, when combined with our control for prior cognitive function, is that pre-retirement ICT exposure does not directly affect post-retirement cognitive decline. The included controls for education and prior cognitive performance imply that past exposure should not be a function of the skill level or capabilities of the worker. Later, we demonstrate that our IV estimates are concentrated amongst workers in middle-skill occupations where many routine tasks coincided with unexpected shocks of computerisation at the workplace. More detailed descriptive information about the uneven spread of computerisation across industries and occupational groups is provided in Section 4.4.

As a result of data availability, the measure of past ICT exposure in this study is a binary variable of whether the individual used a computer or a tablet in the last job before retirement. Our instrumental variable does not directly relate to any density or working skills of computer use at the workplace before retirement. Essentially, our underlying identifying assumption is that pre-retirement ICT experience enhances the likelihood of internet in later years, conditional on a set of rich controls for individual characteristics such as education, cognition level and health that are typically considered influential factors in occupational choice. It is possible that cognition affects computer usage within occupations; for example, a high functioning worker within an occupation or organisation could have been sorted towards tasks that involved computer usage. However, crucially, we control for prior cognitive function, and thus, we control for effect of cognition on computer use to some extent. In the following results section, we also implement Oster (Oster 2019)(93) tests to examine the coefficient stability of the link between our instrument and current internet use. Then we further examine the resource of ICT exposure by exploring alternative versions of this IV to rule out the impact of individual unobservables, as well as likely sources of violations of the exclusion restriction. Moreover, we estimate analogues of equations 4.2 and 4.3 to model the relationship between current and prior cognitive function.

One additional concern is the differences in retirement age patterns across individuals. Our main approach to this is to restrict the sample to those who have consistently reported retirement since the year 2004 and had no paid work in the last four weeks. This sample restriction helps reduce the impact of endogenous retirement that has been a focus of recent literature (Banks *et al.*, 2010(11); Mazzonna and Peracchi 2012(87)). Further robustness checks on the potential endogenous retirement are also provided in Section 4.4.

4.4 Results

4.4.1 OLS Estimation

In this section, we present results about the impact of internet use on the performance in the delayed recall test. The unconditional correlation between internet usage and the number of words recalled in the delayed word recall test using the internet is 0.723 of a standardised deviation increase in the delayed word recall test, approximately 1.3 more words recalled from a list of ten words (see Appendix Table 4.14). Adding past cognition performance tested two years ago significantly drives the coefficients downwards by over 50%. A positive impact of internet use on the delayed recall test is still significant at the one per cent level even after controlling for other relevant variables.

The other relevant variables are: schooling years, household income, country fixed effects, work experience, retired years, marital status, living area, household and health conditions. The higher order of age is also included to capture the potential non-linearity in cognitive function. Besides, the presented specification does not include variables about their life quality or mental condition such as depression. Otherwise potential endogeneity occurs as internet is suggested as helpful in alleviating negative feelings of isolation among older people. In fact, including relevant measures such as the Control, Autonomy, Self-realisation, and Pleasure (CASP) scores and the depression score (Euro-d) only slightly affects the estimates. The standard errors are clustered at a household level.

The first two columns in Table 4.3 show our estimates based on the full working sample: the estimates indicate that individuals who currently use the internet can recall 0.5 more words in the delayed recall test. The size of the coefficient is in line with that in the second column which uses the standardised number of words as the outcome variable. The internet usage is associated with an increase of around 0.2 of a standard deviation in the delayed recall test.

There are significant differences between genders in the delayed recall test and internet usage; the mean score of the recalled words measured in the year 2015 for the male is 2.99 on average and is statistically smaller than that of females (3.21). 35.2% of males reported internet use, and the figure is only 21.0% for the female. So we split our sample by gender and present separate regressions. For females, the estimated average impact of internet use is 0.27 of a standard deviation increase in the delayed recall score, which is 30% higher than that of the male.

4.4.2 IV Estimation

Our estimates of the relationship between internet usage and the delayed recall test might reflect correlation rather than causation. Both internet usage and performance on the delayed recall test might be affected by a third unobserved variable. Even if there is no third variable, it is difficult to establish the direction of causality between internet usage and performance on the delayed recall test.

To establish causality, we model internet usage at the time of the survey as a function of computer usage in their previous jobs. Our key argument is that computer use in previous jobs provides plausibly exogenous variation in the likelihood of internet usage after retirement. The specific group in the SHARE sample, who were born before the 1960s, were trained in computers after they entered the workplace, and the computerisation of workplaces occurred at different speeds in the past 30 years. In the absence of a standard measure of computerisation within workplaces, we use the variation in the proportion of computer users in the respondents' last job before their retirement to approximately represent computer usage intensity.

Figure 4.3 reflects variations in the mean of computer use in the last job before retirement at an industry level based on our working sample. Unsurprisingly, computer manufacturing/retailing industry ranks the highest in the average computer usage in the workplace with over 80% of those working in that industry reporting that they used a computer, which is significantly higher than the population average of 26%. In our sample, some high-ranking industries (NACE-industry) are computer and related activities, financial services and research and development. Most manufacturing jobs are near the middle range of our ranking of ICT use, and computers seem scarcely used in jobs such as recycling and agriculture. However, past PC use in work does not always perfectly predict their current internet use: people from the fields such as R&D, education and real estates are more likely to use the internet in their current life. From a more detailed perspective of occupations, computer use is more required in professional and technical jobs, and managerial jobs as well, as shown in Figure 4.4. There are also a few occupations that have significantly more ICT use in subsequent retired life such as armed forces, life sciences and health and teaching. Particularly, people who rarely use a computer in their last job do not have as low ratios of internet use as their computer use in jobs, suggesting the potential endogenous choices of internet use after retirement to a certain degree.

Arguably, pc use in the workplace is endogenous when people select themselves into various occupations. While our first-stage regression has included a rich set of controls for individual characteristics and past cognition function, other influential confounders might exist such as innate abilities, past working experience, personality, and external economic or health shocks. Some of these may be unobserved or cannot be perfectly captured in our regressions. Therefore, we further test the degree of selection bias caused by unobserved confounders using an Oster test (Oster 2019)(93) which takes account of the movement of R^2 and provides a lower bound estimate[7] of our first-stage relationship. The first six columns in Table 4.4 show the adjusted estimates under a set of arbitrary δ corresponding to different proportionality of the selection on unobservables. Column (1) restates our main first-stage coefficient of the impact of pre-retirement computer use on current internet use assuming no selection effect due to unobserved confounders. Column (7) presents the critical δ that makes the coefficient zero, i.e., the degree of selection on unobservables necessary to explain away the estimate. Panel A shows results for our baseline IV estimation. As δ increases, the adjusted-estimates are generally smaller than the original coefficient in column (1). Although the estimate decreases by around 50% under the assumption of equal selection on unobservables relative to observables, the estimated effect of past pc use is still large. Indeed, the correlation between our instrument and endogenous internet use variable would only fall to zero if the degree of selection on unobservables is 1.5 times large compared to the selection on observables. Panel B, C and D report results in subsamples divided by countries, current cognitive level (the year 2013) and the skill level of the last job before retirement. These divisions help accommodate more heterogeneities that might be related to unobserved confounders and the sources of exogenous variation in our identification method. In general, all the first-stage coefficients of our instrument do not vary substantially, and most adjusted estimates are approximately more than half of our original estimates even assuming the equal importance of unobservables. Although we still cannot identify other sources of potential selection, especially short-term shocks that may affect current ICT use, the evidence above supports the link between ICT use in the workplace and post-retirement life.

Table 4.5 offers our instrumental variable estimation results. First, the linearly estimated coefficient of our instrumental variable is 0.305 and is significantly positive at the one per cent level, conditional on a variety of individual characteristics relating to cognition, income, education, health and household. The logistic regression shows that the average marginal effect of using a computer at workplace increases the probability of using the internet by 16.9%, which is higher than the influence from gender (8.5% for being male), age (-0.6%), and schooling year (1.3%). A clearer picture of the first-stage correlation between computer usage in the respondent's previous job and internet usage in retirement is provided in Appendix Table 4.15. Negative correlations are found in physical inactivity and the number of people in the household.

Our instrumental variable estimation indicates a consistently positive impact of using the internet on cognitive performance. Firstly, the estimates using a binary instrument of PC use at the last job before retirement gives an estimate double that OLS estimates based on the same sample, equivalent to an improvement of near one more word in the delayed recall test which ranges from 1 to 10. The first-stage F statistic is 227.36, suggesting a relative bias of IV to OLS within 5%. The test also implies that less than 5% IV estimates would reject the hypothesis that the coefficient is zero under the 5% significance level. Regarding the gender difference, we observe a similar pattern that females are potentially more positively affected by the internet even though they might be less familiar with ICT in the workplace or everyday life.

Table 4.6 presents further estimates suggesting a positive impact of current Internet use on other cognitive outcomes such as the immediate word recall which also partially captures the short-term attention and memory function. The estimates are smaller in magnitude than those associated with main outcome. In light of a potential long-term impact, we test the delayed word recall score measured two years later (the year 2015): the coefficients are still persistently positive suggesting an increase of around 0.2 of a standard deviation in OLS estimation and 0.4 in IV estimation.

Moreover, we include a continuous variable of working years in the final job before retirement and an interaction term as attempts to capture the potential exposure impact of working habit that promotes ICT familiarity and usage (see Appendix Table 4.16). It is shown that the estimates are persistent and hardly affected. In other specifications, we use more occupation-based variations of computer usage to instrument current internet use and find a consistent positive impact on cognition.

There might be a concern that the last job before retirement may be less affected by the computerisation if individuals have other jobs as their main career that are expected to be more influential. In our sample, it is difficult to track their main career precisely and to keep a large sample size simultaneously. Alternatively, we further restrict our sample into subgroups that are probably more related to the transmission of ICT use at the workplace, and observe the stability of our IV estimates. As shown in Table 4.7, the first group excludes people who never worked because we fitted a zero value for their pc use at the workplace in main IV specification. In the second and third group, we further restrict our sample to the people who were less affected by potential endogenous factors or negative shocks by imposing a condition of statutory retirement. Both OLS and IV estimates are still around 0.2 and 0.4 of a standard deviation. In the last group, we conduct our estimation in the sample of people who started last job before 1980 and retired later. These people are potentially more affected by the large-scale computerisation in the workplace after 1980. Then, we add a constraint on their working years to exclude the noises of temporary jobs that may weaken the linkage between the working pc use and subsequent internet use. In fact, the average working year of the last job before retirement is more than 20 years, which addresses the concern over the possible difference between their last and main career job. In all, the coefficient of internet use is stable and consistent across these groups.

It should be emphasised that the estimates above only give the local average treatment effect (LATE) that does not take account of people whose current internet use is not affected by their past use at the workplace. Given the monotonicity assumption, the size of the compliers could be measured by the first-stage difference in the probability of having the treatment. In our sample, the compliant population is 24.8% [8] of the treated population, suggesting less concern over the small fraction of compliers. Due to the counterfactual problem, it is impossible to identify the exact compliers that are monotonically affected by our instrument. Instead, we use the variation in the first stage across covariate groups to describe some characteristics of the potential compliers. Table 4.8 illustrates compliers characteristics ratios for gender, age, schooling, early childhood condition, occupation and health. For some Bernoulli-distributed characteristics, the relative likelihood a complier has the characteristic indicated in the first column is given by the ratio of the first stage for the observations with the characteristic to the overall first stage (Abadie 2003(1)). There is some evidence that the compliers may come from a disadvantaged background as they are less likely to have more income, schooling years, better language performance at their age ten, or take high-skilled occupations, compared to the average in the sample. The proportion of people with a health problem also appears to be high among the compliers.

These results help explain our larger LATE compared to the OLS estimate, which might be partially explained by the exclusion of the people who might form their internet habit more for entertainment purposes. By comparison, the current internet users who bring their working habit into later life to some extent might use the internet more proficiently and constructively and receive relatively more benefit than they would do otherwise. Ultimately, these findings support the view of beneficial ICT among older people and lead us to consider possible mechanisms further.

4.5 Robustness Checks

A valid instrument is correlated with current internet usage but otherwise uncorrelated with cognitive function itself or other omitted variables that influence cognition. In this section, we compare several estimates among a range of subgroups of populations to check the external validity restriction of our IV estimates.

4.5.1 Endogenous Education

One concern is that our estimates are driven mainly by the people from a relatively advantaged background. People with more schooling or better ability are more likely to select skilled occupations that involve more computer usage in their intellectual work. In the subgroup analysis of education qualification, we present results of three combined categories considering the small sample size in the initial 6-category measure "International Standard Classification of Education (ISCED)". The impact of using the internet for people with only pre-primary or primary qualifications is almost equally as much as that for people who obtain at least a bachelor degree. In addition, we divide our sample into two main groups by a cut-off of ten years, which approximately corresponds to the compulsory schooling years across Europe before the 1970s. As shown in the last four columns of Table 4.9, the OLS estimates are close, but the IV estimates are even more significant for those people with fewer schooling years given a similar sample size of these two groups. Another strategy is to use early childhood conditions as controls for latent abilities that lead to endogenous education and occupation choices. By adding controls for the number of books at home, the language and maths performance at age ten, we still observe a similar pattern, and the impact of using the internet is around 0.20 of a standard deviation in OLS and 0.40 of a standard deviation in IV estimates (see Appendix Table 4.17).

4.5.2 Age, Cohort Effects and Retired Years

A second concern comes from the age effect concerning cognitive decline and ICT attitudes and real use. The younger cohort presumably holds more positive attitudes towards new technology and are more exposed to the technological change in the workplace after the 1980s. In our data, the younger cohort aged under 70 in the year 2013 reports more ICT usage: 36% of them use the internet, but the figure is no more than 30% among the people over 75. Table 4.10 presents the corresponding subgroup analysis. The IV estimates are less accurate for the older people because of a weaker effect of computerisation at the workplace. In general, the OLS estimates are similar across age groups and exhibits a slightly upward trend. The marginal effect of ICT use might be greater for the older group with fewer ICT experience. Also, this might correlate to a positive selection effect as they might hold a more positive attitude towards new technological tools and general life as well. Moreover, we divide the pooled sample into three cohorts with a set of dummies as controls for potential cohort effect. The reference cohort is the one born between the Second World War (1939-1945). Controlling for cohorts rarely affects our estimates as nearly 70% of the population are born before the Second World War (see Appendix Table 4.17).

Finally, it is likely that the impact of internet use diminishes with the years after retirement, especially when the ICT use comes from previous working habits. The lower panel of Table 4.10 manifests that the impact of internet use is not higher for the group of people who retired less than ten years. Instead, the transfer of ICT use from workplace to retired life can be persistent in the long term.

4.5.3 Occupation Characteristics

The external validity of our instruments might be affected by unobservable attributes that cause people to select into occupations. Different occupations might partially affect the cognitive and non-cognitive outcomes of workers because of the tasks and skills that are specific to those occupations. To account for the characteristics of occupations, we firstly add dummies of employment types that indicate whether the person's final job before retirement was self-employment or as an employee in the public or private sector. Regardless of some differences in cognitive scores and computer usage, the results are largely unaffected (see Appendix Table 4.18). Then, we add a set of occupation dummy variables to the model to further control for job characteristics. After controlling for occupation, we still find that internet usage is associated with approximately 0.4 of a standard deviation increase in the cognition scores. Similar results are obtained when we control for parental occupation so as to account for the influence of parents on the occupation choices of the next generation.

Furthermore, we sort occupations by different skill levels according to ISCO-code into four groups[9]: elementary, medium-level, technicians and associate professionals, and professionals, in accordance with the official guide of ISCO (International Labour Organisation,1990). In line with common perception, the more skilled jobs are associated with higher cognition scores, income, education and a higher proportion of computer and internet users. The OLS estimates (see Appendix Table 4.18) are consistently positive among all groups, but the IV estimates are substaintially higher for the medium-skill group that refers to jobs such as clerks, service workers, sales, craft workers and machine operators. Consistent with the research on the skill-biased technology change that primarily substitutes the middle-skilled occupations (Autor *et al.*,2015(31)), the ICT use at the workplace is partially inherited and contributes to a better cognition performance.

4.5.4 Other Leisure Activities

It is possible that internet users are relatively more active in a variety of leisure activities that may promote cognitive functioning. By internet use, there exists a statistically significant difference in aspects of reading newspapers/magazines and going to social/sports clubs (see Appendix Table 4.13). In our main regression, we do not include controls for other activities because of a high number of missing values. However, we include controls for reading behaviours and still obtain statistically significant estimate: 0.25 of a standard deviation in OLS regression and 0.55 in IV regression. In addition, over 80% individuals report their every-day reading. It is plausible that many leisure activities such as reading, playing games or going to clubs are rather stable habits that could have been properly absorbed in the past cognitive score in our specification. Therefore, our results are less affected by considering other activities and demonstrate a separate effect of internet use - a relatively new activity since the year 2010[10].

4.5.5 Specification Checks

Columns in Table 4.11 explore the robustness of our core results to changes in different model specifications and a set of alternative control variables. In the upper panel, we test three alternative models that hinge on different assumptions. Model A does not include the past cognitive outcome and presents a contemporaneous relationship between current internet use and cognitive outcome. In this specification, the estimator relies on a rich set of observed controls that sufficiently capture the latent abilities or other factors. In comparison with our main value-added specification (Model B), Model A gives almost twice as large estimates in magnitude, implying limited power in controlling for unobserved factors that affect both internet use and cognitive score. The following models focus on the change of cognitive score between the year 2011 and 2013, which essentially assumes an age-constant impact of omitted factors on cognitive functioning. Model D relaxes that assumption of an age-constant impact and further includes past outcomes as a control for potential serial correlations of the error term. As seen in the last four columns in the upper panel of Table 4.11, the results are discrepant and statistically insignificant in Model C. This might be explained by the ceiling effect as there is limited space for improvement in test score for the individuals who already achieved a high score. Thus, Model D includes their past cognitive score as an essential control for baseline cognition level and has profoundly increased the explanatory power as well.

The lower panel of Table 4.11 presents the results of alternative controls to some key covariates that might be vulnerable to measurement error. The household total annual income is replaced with the household assets that cover both tangible and financial assets at the household level. Then, we used the distance to the national statutory retirement age to reduce the impact of the inaccurate report of retirement year in the following two columns. The effect of internet use is also robust to adding more controls for mental status and partners' effect. The coefficients of current internet use remain around 0.2 of a standard deviation in OLS and 0.4 in IV.

4.6 Conclusion

To date, there are only correlational studies reported based on large social survey data in gerontology and psychology about how technology affects the well-being of older people (Lelkes *et al.,*2013(76) , Heo *et al.,*2015(67)). Using a large longitudinal dataset of older people living in European countries, we investigate the relationship between internet usage and cognitive decline. Our research extends previous correlational studies by contributing to a plausible causal relationship. We address the issue of omitted variable bias and selection into post-retirement internet usage by using the exposure to computers in the workplace before retirement as an instrumental variable. The validity of our instrumental variable is based on the sample entering the workplace before large-scale computerisation when some encountered the introduction of computers to their workplace while others did not.

On the whole, we find a consistently positive impact of using the internet during retirement on cognition among older people. Using information from the first, fourth and fifth waves of SHARE, we estimate models based on a restricted sample of people aged fifty or older who have been retired since 2004. To help reduce the effect of endogenous early retirement, we focus on the cognitive outcomes measured after nine years of retirement.

The OLS estimates show that internet use in retirement is associated with an increase of 0.23 of a standard deviation in the delayed word recall test, an increase roughly equivalent to half a word. We find a larger and positive impact that is equivalent to nearly one word in the delayed recall word test when we use occupational-level computer use in the final job before retirement as instruments for internet use after retirement. In general, conditional on a rich set of controls for demographic characteristics, education, health, past cognitive performance and household characteristics, all OLS and IV estimates are consistently positive and statistically significant at the one per cent level. In addition, it has been found that females were more affected by internet use in retirement.

Moreover, there is not any conclusive evidence that the effect of internet use is higher for people from advantaged backgrounds or younger cohorts. Although common social-economic factors such as education and income greatly affect general ICT use, the he subgroups of lower levels of schooling seem to have benefited more from internet use. We also find some evidence that computerisation of the workplace affected middle-skilled occupations such as clerks, service and craft workers, a finding which is consistent with research on the job-polarisation and skill-biased technology changes (e.g.Autor *et al.*,2003(9), 2015(31); Goos *et al.*,2014(61)). The positive impact of internet use is seemingly insignificant for the high-skilled people who presumably use more computers at the workplace. To explain these discrepant results, we could consider the heterogeneous impact of computerisation at work. For the occupations that involve more routine tasks, the increasingly applied ICT in this sector is likely to introduce additional cognitive stimulation and challenge that might facilitate their retirement life. While the group of professionals with better adaptability to technological changes may naturally keep their active thinking and learning style all the time, which might not be particularly related to extra benefits of ICT use.

One limitation of this study is that the SHARE dataset has insufficient detail about how and why the older people are using the internet. Thus, it is impossible to say whether the cognitive benefits are coming from, for example, improved social connections, stimulation from online entertainment, or increased availability of information about health. Surveys suggest general surfing and browsing and communication as main activities among internet users in the UK[11]. Nevertheless, although our findings show that internet use improves cognitive performance among the elderly, more research is needed to identify the causal mechanism.

The European Commission has proposed relevant policies and programmes for ageing well with ICTs. Many efforts are dedicated to improving the digital healthcare system, living assistant tools among patients and healthcare workers. Also, there are increasing attention on the ICT support on the independent living of older adults such as Using Internet of Things (IoT) which features an integrated digital ecosystem. In line with this orientation, our results provide causal evidence of the cognitive benefits of digital inclusion in the elderly's daily life. Although our results may be less directly linked to clinical implication on specific cognitive disease, a strong positive effect on general cognition is likely to introduce further associated well-being and health benefits. In parallel with some cutting-edge technologies in progress, it could be equally beneficial for government and communities to simply encourage more digital engagement as part of a new beneficial activity. Practical interventions could empower the elderly by introducing formal or informal learning opportunities, at various levels for people in need.

4.7 Tables and Graphs

Table 4.1: Sample Selection and Descriptive Statistics

Panel A: Sample Selection

Wave Participation	**Interviewed**	**Age>=50**	**Retired**	**Neverwork**	**Total**
Wave 1 (year 2004)	30434	29242	13416	2433	15849
Wave 1 & 4 (to year 2011)	12478	12427	6960	957	5335
Wave 1 & 4 & 5 (to year 2013)	9902	9884	6057	760	3924

Panel B: Sample Characteristics

	Working Sample		**Comparison Sample**		**Difference**
	Mean	N	Mean	N	t-test
Delayed Word Recall (year 2013)	3.11	3798	4.25	6086	1.13***
Numeracy Score (year 2013)	3.30	3798	3.61	6086	0.30***
Uses Internet in past 7 days	0.27	3798	0.59	6056	0.32***
Used Computer in the final job before retirement	0.22	3798	0.49	3410	0.22***
Male	0.45	3798	0.42	6086	-0.04***
Age (in year 2013)	77.16	3798	67.76	6086	- 9.39***
Retirement Year	1995	3083	2002	4148	8.27***
Retired Years	17.43	3798	10.07	4218	- 7.37***
Working Years of the final job	26.17	3072	17.10	2579	- 9.06 ***
Neverwork	0.19	3798	0.01	6086	- 0.18***
Schooling years	9.74	3798	11.35	6086	1.61 ***
Annual income	23184	3798	26753	6086	5369***
Large city (Residence)	0.10	3798	0.10	5784	0.001
Married, living with spouse	0.64	3798	0.69	6086	0.05***
BMI (year 2013)	26.65	3798	26.64	3798	- 0.02

Note: *** significant at 1% level; ** at 5% * at 10%. This table illustrates details in our sample selection: group of people who have been retired since the year 2004. Because of missing variables, we have a working sample of 3798 in the main analysis. In the lower panel, the comparison group is the people who are aged over 50 and also participated in all waves 1,4 and 5. In comparison with our retired group, they were working or doing other temporary paid jobs during the survey time until 2013. The last column in the lower panel reports the difference of the mean measures across two samples. For those who never worked, years retired were replaced with years since reaching national statutory retirement age. The measure of household income is an imputed measure based on fully conditional specification method and is obtained by aggregating at the household level all individual income components. More details could be found in the SHARE working paper by Bertoni *et al.* (2016)(85).

Table 4.2: Summary Statistics by Countries

Country	**N**	**Delayed Word Recall**	**Uses Internet**	**Used PC** in final job	**Sustained Retired** (% of respondents)	**Never Worked**
Austria	269	3.74	22%	25%	49%	11.9%
Germany	247	3.56	30%	26%	35%	4.9%
Sweden	356	3.30	38%	45%	32%	0.6%
Netherlands	272	3.32	47%	30%	24%	19.9%
Spain	465	2.04	62%	3%	45%	50.5%
Italy	622	2.59	9%	9%	55%	28.5%
France	507	3.31	33%	27%	47%	8.7%
Denmark	250	3.68	49%	30%	33%	1.2%
Switzerland	122	3.38	32%	30%	27%	9.8%
Belgium	688	3.34	33%	22%	41%	20.9%

Note: The table is based on 3798 observations in our working sample. The sixth column shows the proportion of retired people (keep retired in all the first, fourth and fifth waves) in the eligible participants who participated in the selected three waves.

Table 4.3: OLS Estimation of the Effect of Internet Use on Cognitive Test Score

Outcome (Y_t): Delayed Recall Test Score (year 2013)						
	Grouped		**Male**		**Female**	
	Y_t	stdY_t	Y_t	stdY_t	Y_t	stdY_t
Method	OLS	OLS	OLS	OLS	OLS	OLS
Uses Internet (D=1)	0.487***	0.233***	0.430***	0.205***	0.557***	0.266***
	(0.071)	(0.034)	(0.098)	(0.047)	(0.103)	(0.049)
Y_{t-1} (year 2011)	0.456***	0.451***	0.400***	0.396***	0.495***	0.489***
	(0.016)	(0.016)	(0.024)	(0.024)	(0.021)	(0.021)
Age	-0.064	- 0.031	-0.127	-0.061	-0.034	- 0.016
	(0.064)	(0.030)	(0.101)	(0.048)	(0.083)	(0.040)
$Age^2/100$	0.024	0.011	0.067	0.032	-0.003	-0.001
	(0.041)	(0.019)	(0.064)	(0.031)	(0.054)	(0.026)
Male	-0.317***	-0.151***				
	(0.068)	(0.032)				
Schooling Years	0.048***	0.023***	0.054***	0.026***	0.040***	0.019***
	(0.008)	(0.004)	(0.011)	(0.005)	(0.012)	(0.006)
Income (top 25%)	0.251**	0.120**	0.320*	0.153*	0.213	0.102
	(0.120)	(0.057)	(0.188)	(0.090)	(0.155)	(0.074)
Other Controls						
Ever worked, Years Retired	√	√	√	√	√	√
Health	√	√	√	√	√	√
Household Characteristics	√	√	√	√	√	√
Country Fixed Effects	√	√	√	√	√	√
R^2	0.3898	0.3898	0.3442	0.3442	0.4411	0.4411
N	3798	3798	1717	1717	2081	2081
N-clusters	3199	3199	1717	1717	2076	2076

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are in parentheses. There are 3,199 clusters for the grouped observations, 1,717 for male group, 2076 for female group. Health controls are standardised body mass index, standardised number of doctor visits, whether has long-term chronic disease, whether has physical inactivity, whether drink (more than two glasses) every day and whether smoke every day. Regression also includes controls for years retired. For those who never worked, years retired were replaced with years since reaching national statutory retirement age. Household characteristics are controls for marital status, household size, living area (urban, rural, or town), house ownership, whether living in nursing house, and four quantiles of total household income (transformed using PPP index).

Table 4.4: Oster Test on the First-stage Relationship

				δ			δ	N
	0	0.25	0.5	0.75	1	1.25	($\theta = 0$)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Estimation								
All observations	0.305	0.267	0.229	0.189	0.143	0.087	1.518	3798
Male	0.290	0.249	0.208	0.165	0.116	0.055	1.414	1717
Female	0.302	0.271	0.240	0.206	0.168	0.124	1.685	2081
Panel B: By Country								
Central Europe	0.287	0.256	0.225	0.193	0.157	0.115	1.691	2105
Scandinavian Country	0.255	0.228	0.202	0.173	0.141	0.105	1.716	606
Mediterranean Country	0.361	0.327	0.293	0.256	0.214	0.162	1.641	1087
Panel C: By Current Cognitive Level								
Cognition (lowest 25%)	0.330	0.294	0.259	0.222	0.180	0.128	1.607	1473
Cognition (25%-75%)	0.268	0.239	0.209	0.178	0.143	0.103	1.679	1844
Cognition (highest 25%)	0.321	0.300	0.278	0.252	0.224	0.189	1.871	481
Panel D: By Skill Level(the final job)								
Elementary	0.177	0.158	0.139	0.118	0.095	0.071	1.798	338
Medium	0.296	0.271	0.246	0.219	0.189	0.154	1.818	1457
Technician and Professionals	0.266	0.240	0.212	0.182	0.149	0.110	1.679	862

Note: This table shows how our first-stage estimate of the impact of past computer use (θ in equation 4.3) on current internet use might be sensitive to selection on unobservables. δ measures proportionality of selection on unobservables relative to selection on observables. Columns (1) to (6) present bias-adjusted estimates calculated by $\widehat{\beta} - \delta * (\beta' - \widehat{\beta})(R_{max} - \widehat{R})/(\widehat{R} - R')$, where $\widehat{\beta}$ and $\widehat{R}$ are the coefficient estimate and R^2 from a controlled regression, and β' and R' are from an uncontrolled regression. Column (7) presents the δ that makes the first-stage estimate of θ zero. A reasonable R_{max} is set to be $1.3 * \widehat{R}$ as suggested by Oster(2019)(93).

In Panel B, Central Europe includes Austria, Belgium, Netherlands, France, Germany and Switzerland. Scandinavian countries include Denmark and Sweden. Mediterranean countries include Italy and Spain in our sample. In Panel C, cognitive level is divided by the delayed recall test score in the year 2013. In Panel D, occupation skill level is defined by the International Labour Organization (ILO). “Elementary” group covers occupations whose main tasks consist of selling goods in street, doorkeeping, cleaning, pressing in the fields of agriculture, fishing, mining, construction and manufacturing. “Medium” group includes clerks, service workers, shop sales, skilled agricultural and fishery workers, craft and related trade workers, plant and machine operators and assemblers. The last group includes “professional” occupations that require a high level of professional knowledge and experience, and “technician and associate professionals” whose main tasks require technical knowledge and experience in one or more fields of physical and life sciences, or social sciences.

Table 4.5: IV Estimation of the Effect of Internet Use on Delayed Cognitive Test Score

Outcome (Y_t): Delayed Recall Test Score (year 2013)						
	All observations		**Male**		**Female**	
	Y_t	stdY_t	Y_t	stdY_t	Y_t	stdY_t
Method	IV	IV	IV	IV	IV	IV
Uses Internet (D=1)	0.932***	0.445***	0.669*	0.320*	1.238***	0.591***
	(0.240)	(0.115)	(0.344)	(0.164)	(0.370)	(0.177)
Y_{t-1} (year 2011)	0.442***	0.437***	0.391***	0.386***	0.476***	0.471***
	(0.017)	(0.018)	(0.028)	(0.028)	(0.023)	(0.023)
Age	-0.062	-0.029	-0.113	-0.054	-0.041	-0.020
	(0.063)	(0.030)	(0.101)	(0.048)	(0.083)	(0.040)
$Age^2/100$	0.025	0.012	0.060	0.029	0.005	0.003
	(0.041)	(0.019)	(0.064)	(0.031)	(0.054)	(0.026)
Male	-0.370***	-0.177***				
	(0.073)	(0.035)				
Schooling Years	0.040***	0.019***	0.049***	0.023***	0.032***	0.015***
	(0.009)	(0.004)	(0.012)	(0.006)	(0.012)	(0.006)
Income (top 25%)	0.204*	0.097*	0.292	0.139	0.155	0.074
	(0.123)	(0.059)	(0.189)	(0.090)	(0.162)	(0.077)
IV first-stage coefficient						
Used PC in the final job	0.305***	0.305***	0.290***	0.290***	0.302***	0.302***
	(0.020)	(0.020)	(0.028)	(0.028)	(0.031)	(0.031)
F (Kleibergen-Paap) statistic	227.36	227.51	104.63	104.63	95.63	95.63
Partial R^2	0.085	0.085	0.081	0.081	0.075	0.074
R^2	0.3834	0.3834	0.3419	0.3419	0.4290	0.4290
N	3798	3798	1717	1717	2081	2081

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are in parentheses. There are 3199 clusters for the grouped observations, 1717 for male group, 2076 for female group. Health controls are standardised body mass index, standardised number of doctor visits, whether has long-term chronic disease, whether has physical inactivity, whether drink (more than two glasses) every day and whether smoke every day. Regression also includes controls for years retired. For those who never worked, years retired was replaced with years since reaching national statutory retirement age. Household characteristics are controls for marital status, household size, living area (urban, rural, or town), house ownership, whether living in nursing house, and quantiles of total household income (transformed using PPP index).

Table 4.6: Effect of Internet Use on Other Cognitive Outcomes

Outcome:	**Immediate Word Recall (year 2013)**					
	Grouped		Male		Female	
Method	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.199***	0.303***	0.135***	0.030	0.259***	0.606***
	(0.034)	(0.117)	(0.047)	(0.165)	(0.048)	(0.187)
F-statistic (first stage)		237.33		110.18		100.81
N	3798	3798	1717	1717	2081	2081
Outcome:	**Numeracy (year 2013)**					
	Grouped		Male		Female	
Method	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.184***	0.316***	0.100**	0.252	0.279***	0.460**
	(0.034)	(0.116)	(0.046)	(0.160)	(0.051)	(0.193)
F-statistic (first stage)		233.97		110.89		96.96
N	3792	3792	1714	1714	2078	2078
Outcome:	**Delayed Word Recall (year 2015)**					
	Grouped		Male		Female	
Method	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.217***	0.392***	0.110*	0.355*	0.344***	0.526**
	(0.041)	(0.146)	(0.057)	(0.189)	(0.059)	(0.247)
F-statistic (first stage)		154.45		78.69		56.91
N	2783	2783	1227	1227	1556	1556

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are in parentheses. The raw scores of the numeracy test (ranges from 0-5) were used. The lagged values of numeracy were from 2004 because of the trivial changes in numeracy scores between the 2011 and 2013. Word recall scores were standardised.

Table 4.7: OLS and IV Estimations in Restricted Samples

Outcome : Standardised Delayed Word Recall	**Excluding Never Worked**		**Excluding Early Retired**		**Only Including Retired Around Statutory Age**		**Only Including Retired After 1980**	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.217***	0.422***	0.205***	0.501***	0.173***	0.448***	0.206***	0.390***
	(0.035)	(0.121)	(0.038)	(0.129)	(0.043)	(0.147)	(0.038)	(0.138)
Mean: Y_t	3.2		3.06		3.16		3.26	
Mean: Uses Internet	0.31		0.25		0.29		0.32	
Mean: Used PC in the final job	0.28		0.21		0.27		0.29	
F-statistic (first stage)		197.26		182.95		128.90		149.85
N	3083	3083	3025	3025	2020	2020	2606	2606

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are in parentheses. The instrumental variable is a dummy indicating whether the individual used computer in the final job before retirement. The "early retired" is defined as those who retired at least three years earlier than the average national retirement age."Retired around statutory age" is defined as those who retired within five years of national statutory age. "Retired After 1980" group also restricted to those who worked at least ten years to better capture a sufficient impact of large-scale computerisation at the workplace.

Table 4.8: Complier Characteristics Ratio

Variable	$\mathbf{P}(D_1 > D_0 \mid X = 1)$	**Relative Likelihood**	**N**
Male	0.290	0.951	1717
Age (>80)	0.288	0.944	1203
More than 10 years of schooling	0.237	0.777	1594
Good Language Performance(age 10)	0.236	0.774	420
Higher Income (top 25% percentile)	0.253	0.830	949
High-skilled Occupation (level 1 and 2)	0.266	0.872	863
Chronic Disease	0.313	1.026	3279
Depressed (more than 5 in Euro-d scale)	0.302	0.990	750

Note: *** significant at 1% level; ** at 5% * at 10%. The relative likelihood is given in the third column as the ratio between the first-stage of the selected variable and the overall first stage. The overall first stage is 0.305. The sample contains 3798 observations in total. The high-skilled occupation jobs includes technicians, associate professionals and professionals. The depression is based on the Euro-d scale and the sample average is 2.7.

Table 4.9: OLS and IV Estimation in Subgroups of Education

Outcome: Standardised Delayed Word Recall(year 2013)	**ISCED Categories**						**Schooling Years**			
	Pre-primary & Primary		**Secondary**		**Bachelar& Above**		**<=10**		**>10**	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.237***	0.545**	0.192***	0.337**	0.230***	0.518*	0.267***	0.656***	0.218***	0.256
	(0.071)	(0.267)	(0.047)	(0.172)	(0.073)	(0.305)	(0.050)	(0.151)	(0.048)	(0.196)
Mean: Y_t	2.30		3.42		4.33		2.65		3.75	
Mean: Uses Internet	0.10		0.32		0.58		0.15		0.44	
Mean: Used PC in the final job	0.07		0.29		0.45		0.13		0.36	
F-statistic (first stage)		34.14		91.96		31.76		121.26		77.13
N	1541	1541	1634	1634	623	623	2204	2204	1594	1594

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are shown in parentheses. 1997 version of ISCED codes are used. We have combined a few groups: “Pre-primary and Primary” includes“None” and “Primary or basic education” ; “Secondary” includes lower and upper secondary education, post-secondary non-tertiary education.

Table 4.10: OLS and IV Estimations in Subgroups of Age and Retired Years

Outcome: Standardised Delayed Word Recall(year 2013)	**Age**							
	58-70		**70-75**		**75-80**		**>80**	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.125*	0.520*	0.226***	0.300	0.233***	0.426*	0.251***	0.571**
	(0.087)	(0.278)	(0.067)	(0.226)	(0.063)	(0.253)	(0.064)	(0.246)
Mean: Y_t	3.78		3.55		3.13		2.39	
Mean: Uses Internet	0.36		0.35		0.27		0.17	
Mean: Used PC in the final job	0.27		0.31		0.23		0.12	
F-statistic (first stage)		40.43		63.86		38.90		44.68
N	656	656	947	947	992	992	1203	1203
Outcome: Standardised Delayed Word Recall(year 2013)	**Years Retired**							
	10-15		**15-20**		**>20**			
Method	OLS	IV	OLS	IV	OLS	IV		
Uses Internet (D=1)	0.159***	0.493***	0.328***	0.312	0.222***	0.760***		
	(0.053)	(0.170)	(0.063)	(0.250)	(0.062)	(0.276)		
Mean: Y_t	3.54		3.13		2.57			
Mean: Uses Internet	0.36		0.27		0.17			
Mean: Used PC in the final job	0.32		0.22		0.12			
F-statistic (first stage)		102.08		48.30		36.59		
N	1416	1416	1166	1166	1171	1171		

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are shown in parentheses.

Table 4.11: Specification Check: Models Specification and Alternative Controls

Outcome: Delayed Recall Test Score (year 2013)								
Panel A: Alternative Specifications	Model A		Model B		Model C		Model D	
	std Y_t		**std** Y_t		Y_t - Y_{t-1}		Y_t - Y_{t-1}	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.394***	0.856***	0.233***	0.445***	0.085	- 0.156	0.487***	0.932***
	(0.038)	(0.125)	(0.034)	(0.115)	(0.080)	(0.264)	(0.071)	(0.240)
Y_{t-1}(year 2011)			√	√			√	√
R^2	0.2399	0.2088	0.3898	0.3834	0.011	0.009	0.2666	0.2589
F-statistic (first stage)		254.45		227.51		254.45		227.51
N	3798	3798	3798	3798	3798	3798	3798	3798

Outcome: Delayed Recall Test Score (year 2013)								
Panel B: Alternative Controls					**std**Y_t			
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.233***	0.441***	0.232***	0.433***	0.225***	0.428***	0.223***	0.232*
	(0.034)	(0.111)	(0.034)	(0.115)	(0.034)	(0.116)	(0.041)	(0.139)
Alternative Controls								
Household Asset	√	√						
Distance to statutory age			√	√				
Depression score					√	√	√	√
Partner's age and Schooling							√	√
R^2	0.3894	0.3831	0.3901	0.3843	0.3900	0.3841	0.3728	0.3728
F-statistic (first stage)		243.73		226.79		223.86		145.59
N	3778	3778	3798	3798	3757	3757	2359	2359

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are shown in parentheses. Panel A shows specifications in the framework of value-added model. Model A refers to a contemporary relationship specification that excludes past performance. Model B is our main specification. Model C uses the raw score difference between 2011 and 2013. Model D further includes the past outcomes to control for potential serial correlation of the error term. Panel B shows results when we use alternative controls such as retirement year, household net worth, depression scores (measured by Eurod) in the year 2004, and partner's information.

Figure 4.1: Delayed Word Recall Score (year 2013)

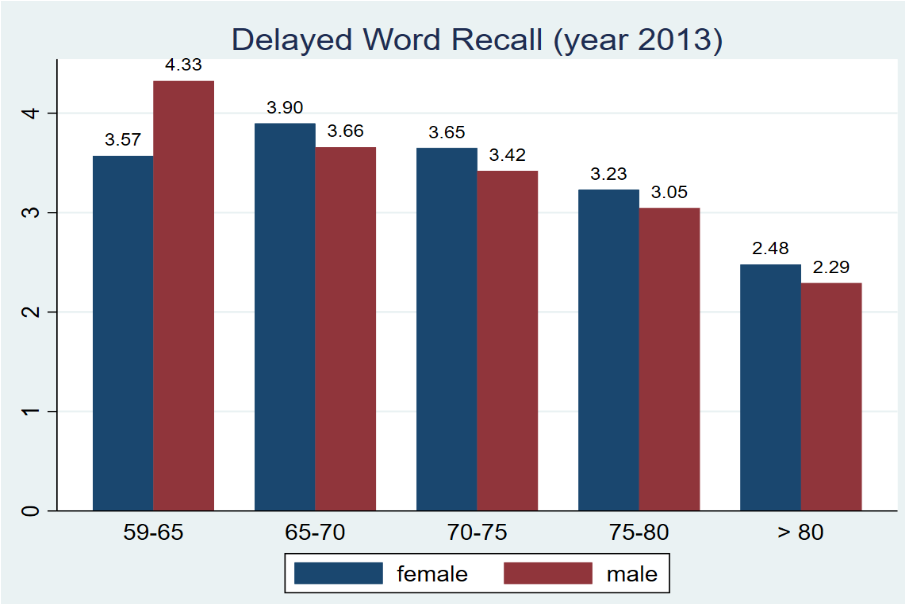


Figure 4.2: ICT Use in Subgroups

Figure 4.3: ICT Use by Industries

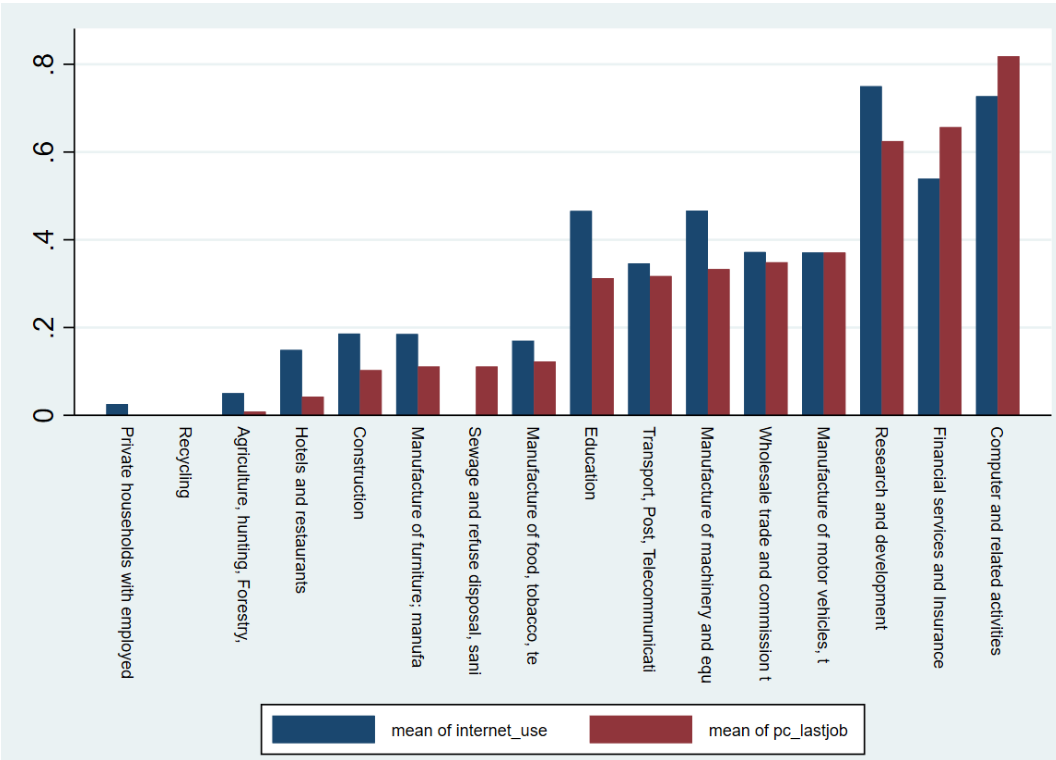
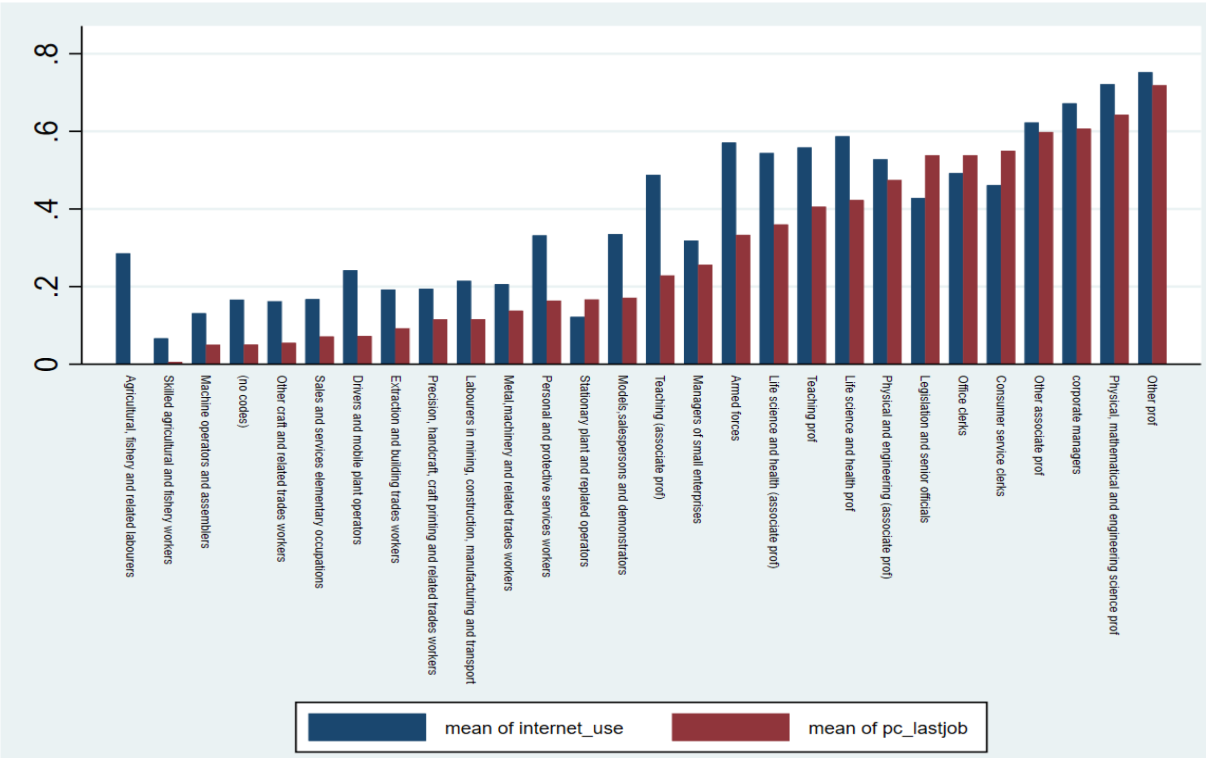


Figure 4.4: ICT Use by Occupations (based on ISCO-88)



4.8 Appendix

Table 4.12: Descriptive Statistics

	N	Mean	S.D	Min	Max	P-value of Diff
Cognitive Measure:						
Immediate word recall (in 2013)	3798	4.57	1.78	0	10	<0.01***
Immediate word recall (in 2011)	3798	4.65	1.75	0	10	<0.01***
Delayed word recall (in 2013)	3798	3.11	2.09	0	10	<0.01***
Delayed word recall (in 2011)	3798	3.27	2.07	0	10	<0.01***
Numeracy (in 2013)	3798	3.3	1.09	1	5	<0.01***
Numeracy (in 2011)	3798	3.3	1.09	1	5	<0.01***
ICT Usage						
Uses internet	3798	0.27	0.45	0	1	
Used computer in final job before retirement	3277	0.26	0.44	0	1	<0.01***
Control Variables						
Male	3798	0.45	0.5	0	1	<0.01***
Age (in 2013)	3798	77.2	7.05	59	102	<0.01***
Year of birth	3798	1936	7.05	1911	1954	<0.01***
Retirement age	3083	59.3	5.71	26	81	0.471
Statutory retirement age (male)	1717	64.5	2.04	60	67	<0.01***
Statutory retirement age (female)	2081	62.3	4.12	55	67	<0.01***
Retirement year	3083	1995	7.24	1957	2004	<0.01***
Years worked in final job	3072	26.17	13.06	0	75	0.188
Never worked	3798	0.19	0.39	0	1	<0.01***
Years of full-time education	3798	9.74	4.46	0	25	<0.01***
Total annual household income	3798	21384	28033	0	895719.1	<0.01***
Resides in large city	3798	0.1	0.3	0	1	0.279
Resides in rural area	3798	0.3	0.46	0	1	<0.01***
Married or living with partner	3798	0.63	0.48	0	1	<0.01***
Widowed	3798	0.26	0.44	0	1	<0.01***
Household size	3798	1.8	0.73	1	7	0.107
Living in nursing house	3798	0.003	0.06	0	1	<0.001***
Own house	3798	0.72	0.45	0	1	0.08*
Body mass index	3798	26.65	4.56	15	67	<0.01***
Drink more than 2 glasses every day	3798	0.1	0.3	0	1	<0.01***
Number of visits to doctor	3798	8.5	10.1	0	98	<0.01***
Physically inactive	3798	0.19	0.39	0	1	<0.01***
Chronic disease	3798	0.86	0.34	0	1	<0.01***

Note: *** significant at 1% level; ** at 5% * at 10%. The values of retirement year, age at retirement, and years worked exclude people who never worked. The last column presents the p-values of difference by current internet use.

Table 4.13: Summary Statistics of Activities

Activities	N	Mean	Mean (Internet User)	Mean (Inactive Internet User)	p-value of Diff
Reading (books, newspapers etc.)					
almost everyday	2660	0.85	0.924	0.818	<0.01***
almost every week	2660	0.12	0.062	0.143	<0.001***
less often	2660	0.01	0.004	0.016	0.002***
Puzzle games					
almost everyday	1587	0.67	0.697	0.655	0.080*
almost every week	1587	0.25	0.233	0.266	0.139
less often	1587	0.03	0.025	0.031	0.462
Card Games					
almost everyday	1125	0.23	0.223	0.229	0.815
almost every week	1125	0.43	0.425	0.429	0.903
less often	1125	0.14	0.129	0.143	0.481
Clubs (sports, social etc.)					
almost everyday	1012	0.13	0.16	0.096	<0.01***
almost every week	1012	0.58	0.585	0.583	0.931
less often	1012	0.08	0.071	0.088	0.303
Voluntary or Charity work					
almost everyday	706	0.18	0.199	0.155	0.122
almost every week	706	0.47	0.479	0.462	0.658
less often	706	0.14	0.114	0.163	0.058*

Note: *** significant at 1% level; ** at 5% * at 10%. The "inactive Internet users" refer to the people who report no recent internet use in recent 7 days. The last column presents the p-values of difference by current internet use. The activities reported here are taken from wave 5 (year 2013).

Table 4.14: OLS Estimation of the Effect of Internet Use on Cognitive Score

Outcome: Standardised Delayed Recall Test Score (year 2013)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Uses Internet (D=1)	0.723***	0.339***	0.316***	0.315***	0.331***	0.255***	0.256***	0.251***	0.240***	0.235***	0.233***
	(0.034)	(0.031)	(0.031)	(0.031)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)
Y_{t-1} (year 2011)		0.530***	0.510***	0.510***	0.506***	0.476***	0.476***	0.468***	0.460***	0.458***	0.451***
		(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
Age			-0.013***	0.003	0.011	0.004	0.003	-0.022	-0.032	-0.034	-0.031
			(0.002)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)
$Age^2/100$				-0.010	-0.015	-0.011	-0.010	0.005	0.012	0.013	0.011
				(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)
Male					-0.069***	-0.087***	-0.097***	-0.141***	-0.164***	-0.156***	-0.151***
					(0.026)	(0.026)	(0.026)	(0.029)	(0.031)	(0.032)	(0.032)
Schooling Years						0.027***	0.026***	0.024***	0.023***	0.023***	0.023***
						(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Household Income (top 25%)							0.085**	0.082**	0.087**	0.095**	0.120**
							(0.038)	(0.038)	(0.038)	(0.040)	(0.057)
Retired Years								0.001	0.002	0.002	0.002
								(0.002)	(0.002)	(0.002)	(0.002)
Never worked								- 0.152***	-0.125***	-0.117***	-0.091**
								(0.040)	(0.040)	(0.041)	(0.044)
Health Controls									√	√	√
Household Characteristics										√	√
Country Fixed Effects											√
R^2	0.1041	0.3560	0.3636	0.3636	0.3647	0.3762	0.3771	0.3797	0.3857	0.3867	0.3898
N	3798	3798	3798	3798	3798	3798	3798	3798	3798	3798	3798

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors clustered at household level are in parentheses and there are 3199 clusters in total. Health controls are physical inactivity, standardised body mass index, standardised number of doctor visits, whether has long-term chronic disease, whether drink (more than two glasses) every day, whether smoke every day. Regression also includes controls for years retired. For those who never worked, years retired was replaced with years since reaching national statutory retirement age. Household characteristics were controls for marital status, household size, living area (urban, rural, or town), house ownership, whether at nursing house, and standardised total household income (transformed using PPP index).

Table 4.15: Instrument Variable Estimation: First-stage Coefficients

First-stage Coefficients	**Whether Uses Internet (year 2013)**			
	Grouped		Male	Female
Method	OLS	Logit	OLS	OLS
Used PC in final job	0.305***	0.169***	0.290***	0.302***
	(0.020)	(0.013)	(0.028)	(0.031)
Cognition Score (year 2011)	0.053***	0.049***	0.068***	0.043***
	(0.007)	(0.007)	(0.012)	(0.009)
Age	-0.013	-0.006	-0.050*	-0.001
	(0.013)	(0.015)	(0.026)	(0.014)
Male	0.092***	0.085***		
	(0.016)	(0.014)		
Schooling Years	0.013***	0.013***	0.016***	0.010***
	(0.002)	(0.002)	(0.003)	(0.002)
Income (top 25%)	0.074***	0.088**	0.068*	0.074**
	(0.024)	(0.035)	(0.040)	(0.031)
Physical Inactive	-0.029*	- 0.064***	-0.020	-0.042***
	(0.014)	(0.018)	(0.026)	(0.016)
Household Size	-0.018**	-0.032**	-0.026*	-0.015*
	(0.008)	(0.013)	(0.015)	(0.009)
Never married	-0.058**	- 0.061*	-0.124***	-0.012
	(0.028)	(0.032)	(0.046)	(0.036)
Suburbs of big cities	0.072***	0.071***	0.085***	0.054*
	(0.022)	(0.020)	(0.032)	(0.028)
Controls	√	√	√	√
R^2	0.3834	0.3341	0.3572	0.3179
N	3798	3786	1717	2081

Note: *** significant at 1% level; ** at 5% * at 10%. Heteroskedasticity robust standard errors are in parentheses. Regressions also include other controls that are similar in our main specification, and this Table only presents a few selected factors of interest. The column of estimated Logit model reports average marginal impact.

Table 4.16: IV Estimation of the Effect of Internet Use on Cognition: Alternative Instruments

Outcome: Standardised Delayed Word Recall (year 2013)						
	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	IV	IV	IV	IV	IV
Uses Internet (D=1)	0.233***	0.445***	0.443***	0.462***	0.778***	0.451***
	(0.034)	(0.115)	(0.115)	(0.113)	(0.155)	(0.149)
Excluded Instruments						
Used PC in final job before retirement		√	√	√		
Years worked in final job before retirement			√	√		
Use PC* Working years				√		
ISCO PC usage mean in final job					√	
ISCO-country PC usage mean in final job						√
R^2	0.390	0.383	0.383	0.382	0.348	0.383
N	3798	3798	3782	3782	3796	3764
Number of Excluded Instrument		1	2	3	1	1
Partial R^2		0.085	0.085	0.087	0.051	0.051
F(Kleibergen-Paap) statistic		227.51	112.51	79.65	155.95	146.82
Overidentification test		pass	pass	pass	pass	pass
Endogeneity test		pass	pass	pass	pass	pass

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors are clustered at household level and are shown in parentheses. In SHARE, the original four-digit occupation code (ISCO-88) has more than 500 categories. We use 44 two-digit ISCO code. For the people who never worked, the variables of pc use in the last job before retirement, and ISCO codes are replaced with zero. All control variables are as same as the main OLS specifications.

Table 4.17: Robustness Check: OLS and IV Estimations with Controls for Childhood Condition and Cohort

Outcome: Standardized Delayed Word Recall (year 2013) *Panel A: Adding Controls for Early Childhood Condition*	**Grouped**		**Male**		**Female**	
	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.211***	0.391***	0.185***	0.252	0.245***	0.541***
	(0.034)	(0.118)	(0.047)	(0.169)	(0.050)	(0.185)
F-statistic (first stage)		212.93		95.86		86.58
N	3798	3798	1709	1709	2074	2074

Outcome: Standardized Delayed Word Recall(year 2013) *Panel B: Adding Controls for Cohort Effect*	**Grouped**		**Male**		**Female**	
	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.230***	0.433***	0.205***	0.315*	0.261***	0.573***
	(0.034)	(0.116)	(0.047)	(0.165)	(0.049)	(0.179)
F-statistic (first stage)		223.17		104.32		93.14
N	3798	3798	1717	1717	2081	2081

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors are clustered at household level and are shown in parentheses. Controls for early childhood condition include the math and language performance, the number of books at home at age ten. Birth cohorts are divided by the Second World War: born before 1939, during the World War, and after 1945. All control variables are as same as the main OLS specifications.

Table 4.18: Robustness Check: OLS and IV Estimations by Occupations

Outcome: Standardised Delayed Word Recall (year 2013)								
Panel A: Adding occupation controls	**Employment Type**		**Occupations**		**Father's Occupations**			
Method	OLS	IV	OLS	IV	OLS	IV		
Uses Internet (D=1)	0.212***	0.452***	0.195***	0.337**	0.224***	0.413***		
	(0.034)	(0.115)	(0.035)	(0.150)	(0.035)	(0.128)		
F-statistic (first stage)		227.79		134.90		182.12		
N	3798	3798	3778	3778	3601	3601		
Panel B: Occupation Skills Level	**1st Elementary**		**2nd Medium**		**3rd Technicians & Associate Profs**		**4th Professionals**	
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.318**	-1.262	0.159***	0.772***	0.215**	- 0.288	0.166*	0.039
	(0.139)	(1.503)	(0.056)	(0.211)	(0.088)	(0.363)	(0.091)	(0.301)
Mean: Y_t	2.31		2.96		3.79		4.19	
Mean: Uses Internet	0.09		0.21		0.45		0.55	
Mean: Used PC in final job	0.05		0.19		0.45		0.43	
F-statistic (first stage)		2.17		75.61		20.21		34.52
N	338	338	1457	1457	437	437	426	426

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors are clustered at household level are shown in parentheses. Employment Type has four categories: employed (public sector), employed (private sector), self-employed, and civil servant (working in government). Panel B controls for Occupation Skills Level. Occupation skills level is defined by the International Labour Organization (ILO). "Elementary" group covers occupations whose main tasks consist of selling goods in street, doorkeeping, cleaning, pressing in the fields of agriculture, fishing, mining, construction and manufacturing. "Technician and Associate Professionals" group includes occupations whose main tasks require technical knowledge and experience in one or more fields of physical and life sciences, or social sciences. "Medium" group includes clerks, service workers, shop sales, skilled agricultural and fishery workers, craft and related trade workers, plant and machine operators and assemblers. "Professionals" group includes occupations whose main task require a high level of professional knowledge and experience. Skill level references are not made in two groups entitled with "armed forces" and "Legislators, senior officials and managers" because other aspects of the type of work were considered more important as similarity criteria.

Table 4.19: Heterogeneity in the Effect of Internet Use by Countries

Outcome: Standardised Delayed Word Recall (year 2013)						
	Mediterranean		**Central Europe**		**Scandinavia**	
Method	OLS	IV	OLS	IV	OLS	IV
Uses Internet (D=1)	0.234**	0.569*	0.257***	0.456***	0.139*	0.414
	(0.093)	(0.297)	(0.043)	-0.153	(0.073)	(0.284)
Mean: Y_t	2.35		3.41		3.46	
Mean: Uses Internet	0.08		0.33		0.43	
Mean: Used PC in final job	0.07		0.26		0.39	
Mean: Schooling years	6.49		11		11.1	
F-statistic (first stage)		35.23		123.13		33.00
N	1087	1087	2105	2105	606	606

Note: *** significant at 1% level; ** at 5% * at 10%. Robust standard errors are clustered at household level shown in parentheses. The instrument is whether use pc in the last job before retirement. Mediterranean countries include Italy and Spain in our sample. Central Europe includes Austria, Belgium, Netherlands, France, Germany and Switzerland. Scandinavian countries include Denmark and Sweden.

Figure 4.5: Starting Year of the Final Job before Retirement

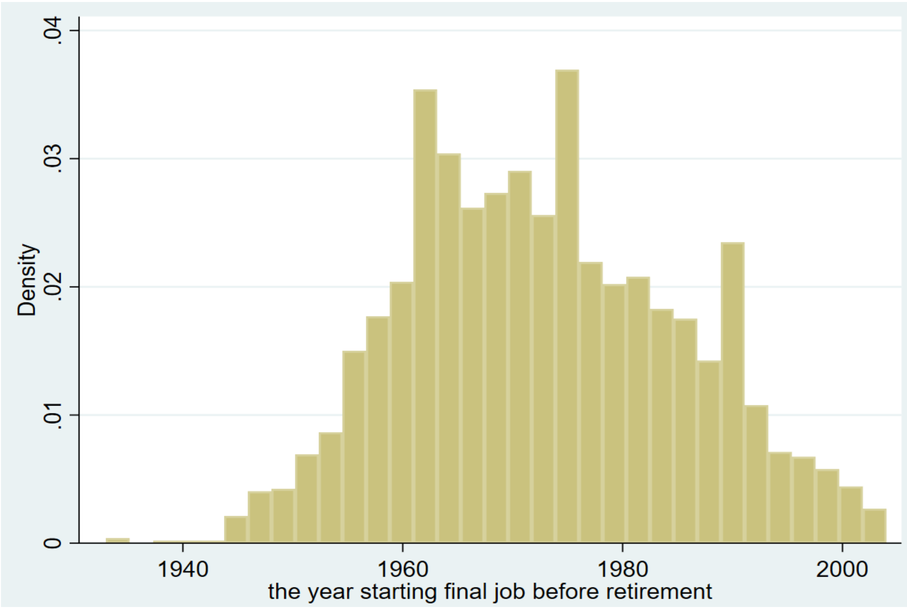
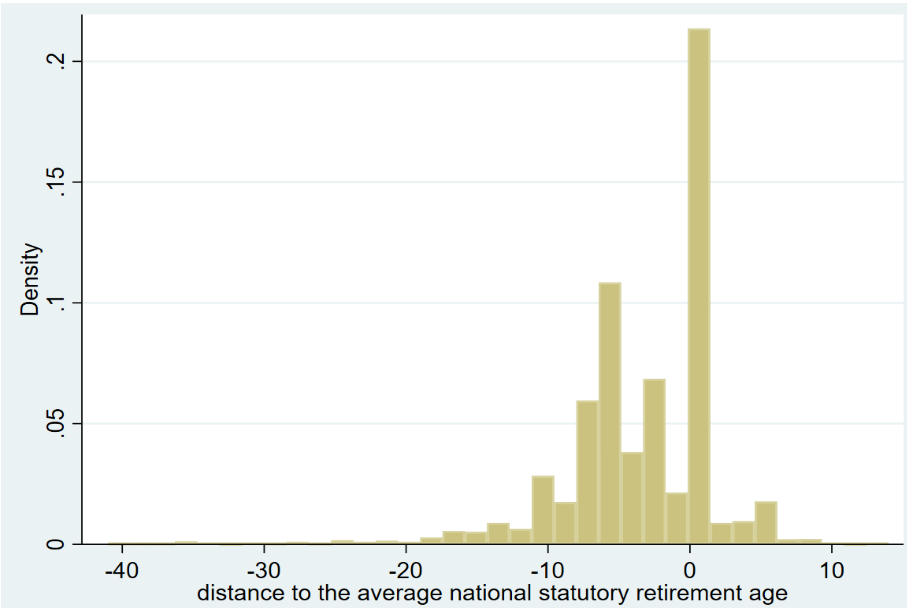


Figure 4.6: Difference between Retired Age and National Statutory Age



Notes

[1]A range of research in gerontology and psychology attempts to explain the determinants of ICT use among older people (e.g. Zheng *et al.*,2015(125); Michelle *et al.*,2014(110)). Education, income, health, and computer experience are significantly predictive of computer and internet usage among the elderly. Similarly, a mixture of qualitative and quantitative studies about the attitudes and perceptions of computer and internet usage among the older people suggest barriers such as the cost of buying equipment, learning difficulties, skeptical attitudes towards computers, lack of social connections, and functional and cognitive problems (Gatto *et al.,*2008(57); Lee *et al.,*2011(75)).

[2]Until wave six (year 2017), there are 21 countries in SHARE survey. But the first wave only constitutes 11 countries including Austria, Belgium, Netherlands, Germany, France, Switzerland, Italy, Spain, Denmark, Sweden and Greece. Israel joined the survey one year later. Eastern European countries such as Poland, Hungary, Czech Republic joined after 2006 and many are missing in the fifth wave. Other eight countries will participate in wave seven (Cyprus, Malta, Romania, Bulgaria etc.) In this paper, we used detailed occupational information which is documented in the first wave, and therefore only have ten countries for our purpose.

[3]In SHARE, the vital status of one respondent is not ascertained because of a lack of a national mortality register in most European countries. Instead, the deceased people were validated by proxy-respondents through end-of-interviews which captures around 70% to 80% valid cases of decease.

[4]ICT development index ranks countries' performance with regard to ICT infrastructure, use and skills. More details could be found in the Measuring the Information Society Report by International Telecommunication Union (ITU) (2014)(120).

[5]In our main specification, the measure of income is a multi-stage imputed outcome that is obtained by an aggregation at the household level of all individual income components. Additional information on the imputation procedure could be referred to De Luca *et al.*2015(32)

[6]As noted by Bresnahan(1999)(18), the diffusion of computer technology application started to increase after the late 1950s. And then the personal computers (Apple II in 1977, IBM in 1981)emerged and spread.

[7]Built on Altonji *et al.,*(2008)(2), Oster derived a general estimator under proportional selection (selection on unobservables is proportional to the selection on observables) with a coefficient of proportionality δ. Under the assumption that the unobservable and the observables are equally related to the treatment variable,the bias-adjusted estimate is approximately given by: $\beta \approx \widehat{\beta} - (\beta' - \widehat{\beta})(R_{max} - \widehat{R})/(\widehat{R} - R')$, where $\widehat{\beta}$ and $\widehat{R}$ are the coefficient estimate and R^2 from the controlled regression, and β' and R' are from the uncontrolled regression.

[8]$P(D_{1i} - D_{0i}|D_i = 1) = \frac{P(D_i=1|D_{1i}-D_{0i})*P(D_{1i}>D_{0i})}{P(D_i=1)} = \frac{P(Z_{i=1})*[E(D_i|Z_i=1)-E(D_i|Z_i=0)]}{P(D_i=1)}$ where D_{1i} refers to the treatment status when Z=1 for individual i. Z is the instrument status. (Angrist and Pischke 2008(6))

[9]There is no skill reference for the groups of "legislators, senior officials and managers" and "Armed Forces" because other aspects of the type of work were considered more important as

similarity criteria, i.e. policy-making and management functions, and military duties.

[10]The data of Eurostat suggests a great expansion of internet users aged between 55 and 64 after the year 2008 : the EU average increased from 45% to 70% in the year 2016.

[11]Internet Users in the UK,the Office for National Statistics, 2016

Chapter 5

Conclusion

Since the past three decades after the arrival of the computer and the internet, it is almost impossible to keep away from the digital and information world. Various forms of Information Communication Technologies (ICTs) are increasingly embedded and integrated into everyday life, bringing up the issue of evaluating their potential impacts on people's well-being. There exist inherent difficulties such as the selection bias and reverse causality in identifying causation between ICT use and human capital outcome. From a methodological point of view, I utilise an array of quantitative tools to deal with endogeneity concerns. Within the broad topic of ICT research, this study aims to shed light upon the effects of many traditional ICTs such as computers and internet on various dimensions of human capital, especially the educational outcomes, cognitive and noncognitive skills.

I start the investigation by considering the impact of ICT use on standard educational outcomes as the updated dimension of educative inputs (such as ICTs hardware and CAI) that increasingly diffuse in the school life of many young students. The research to date has reported mixed evidence of ICT's impact on improving educational outcome. The second chapter of this thesis adds to this discussion and uses a large UK longitudinal dataset, LSYPE, to investigate the impact of one form of home computer investment on university attendance. A home setting enables more flexibility and autonomy in ICT use, which more relates to a student's direct ICT use. By applying a matching strategy to cope with the selection bias, I find that students who received a personal laptop or computer between their age 15 and 17 have a three percentage point higher probability of studying for a university degree at age 18 or 19, conditional on a variety of individual and family controls. This estimate is equivalent to an increase by around ten percentage points in the average university attendance in the UK at the survey time. This causal impact is robust to a range of checks on potential confounders. Regarding possible mechanisms, I incorporate related behaviours (playing pc games, doing schoolwork, reading and ICT school use) as further controls for the underlying ICT-related behavioural patterns and find that educative behaviour such as doing homework on home pc explains around 16 per cent of the treatment effect. Playing computer games hardly affects the estimates, suggesting little offsetting impact.

The widespread ICT-based entertainment draws the attention of researchers and the public to the potential effect of the screen time. Research on the manifold impacts of electronic games has centred in psychological experiments and generated diverse results that vary in different samples and designs. Chapter Three returns to this issue by looking at the relationship between computer games and cognitive and noncognitive development in the early years of childhood - a critical pre-school period for human capital accumulation and early interventions. Based on the Millennium Cohort Study (MCS), this study investigates the impact of playing computer games on developmental outcomes among young children at age three and five years old. I find no evidence that playing computer games worsen children's cognitive and noncognitive outcomes, conditional on rich controls for individual and family characteristics. The OLS and Poisson estimates imply that playing computer games is associated with a decrease of 0.06 of a standard deviation in total noncognitive difficulties, and an increase of around 0.10 of a standard deviation in cognitive tests in pattern construction and picture similarity. Very likely, the gaming behaviour is endogenous and I, therefore, use mother's computer usage at home and new household internet access as external instruments to unfold a causal relationship. Heteroskedasticity-based identification and Conditional Mixed Process (CMP) are applied and also show support to the main conclusion that moderate computer gaming time does not bring a detrimental impact on children's development. Instead, a positive impact on cognitive development appears persistent across different groups.

Chapter Four extends our discussion to another group of people who seemingly stand apart from many evolving modern technologies. This research relates to a growing body of ageing research on how the elderly could sustain a life of high quality. The present chapter investigates the impact of internet use on cognitive functioning among the elderly with an average age over 70. Specifically, our sample has been circumscribed to the people who have retired since 2004, and we test on their cognitive performance nine years later to reduce the impact of endogenous retirement. The results demonstrate that current internet use is associated with an increase of 0.2 of a standard deviation in the ten-word recall memory test, approximately a half more word. The causal impact is established by instrumenting current internet use by past computer experience at the workplace before retirement. The instrumental variable estimates are around twice larger than the ordinary least squares estimates and are not primarily driven by younger cohorts or the people with advantaged backgrounds. Ultimately, our results show a consistently positive impact and are robust to potential violations in the exclusion restriction.

By and large, this thesis has provided plausible empirical evidence of the positive side of ICT use, which advances the understanding of the role of ICTs in people's life from a life-cycle perspective. Results suggest cognitive improvements for the young children around age five and the retired elderly. While for adolescents, whose ICT behaviours are more complicated, could also be positively affected regarding university participation. Based on large social survey datasets that document rich information about people's social-economic information, a range of econometrics tools are implemented to infer better cause and effect relations.

Here, I want to discuss two main aspects on the ground of empirical research presented in this thesis. The first is the behavioural consideration for encouraging ICT-based policies. This thesis has paid much attention to the endogenous ICT use that might closely relate to an individual's inner motivation and other characteristics. The real impact of ICT on delivering education or promoting life quality can be largely dependent on people's actual acts. The increasingly extensive online resources, however, would never be left unexplored for those highly self-motivated people. Therefore, it is of necessity to consider people's abilities and attitudes that help with a better adaptation to the emerging digital world.

The other one concerns the gender disparity in ICT access and usage. As suggested by Chapter Three, such a disparity may not stand out among the very young children regarding their use and cognitive and noncognitive development. Nonetheless, adolescent girls and women seem to have different perceptions and usage of ICT, perhaps as a result of social norms or other cultural factors. Specifically, Chapter Four shows a greater positive impact of internet use for women with less ICT experience from their past careers. In addition to a protective effect on cognitive decline, ICTs still have the potential in encouraging labour market participation after age 65.

A few limitations and cautions appear in this research. First, it is not easy to track more detailed information about ICTs use regarding the intensity, content or purpose. This insufficient information makes it harder to unearth relevant mechanism. Second, the dynamics of human capital development in cognitive and noncognitive outcomes may confine our interpretation of the causal impact of ICT use into more a short-term one rather than a longer-term effect. The mystery of multifaceted human capital development has been consistently inspiring vibrant research. Although beyond the scope of this thesis, I leave these issues for future research.

A few sample features further help us discern the strength of our main conclusion. First, all our data samples are taken in the UK and EU countries, mainly representative developed country that might distinct from many underdeveloped or developing countries. The ICT experience or effectiveness might not hold everywhere. But given the fact of ongoing ICT expansion across the globe, our results are informative for increasing new users in some areas.

Second, some salient cohort features are meaningful in reflecting on many implications of this thesis. The elderly group in Chapter Four, born in the 1950s on average, has almost witnessed the ICT development from a primitive stage to an irreplaceable role in the 21st century. They almost started their interaction with ICT at workplace or home at least in their midlife after IBM invented the first personal computer in 1981. By contrast, adolescents in LSYPE, and the millennium children have a wider range of ICT use such as game consoles and laptops that share most similar functions compared to today. In the meantime, they were experiencing a time of the launch of Facebook, Twitter and Google - a time marked by the increasing expansion of online resources and networking in the first ten years after 2000. The positive impacts of ICT use in this thesis (laptop, video games, basic internet use) are representative and are still persistent in a way in the absence of structural changes in these ICT devices.

Last but not least, some new phenomena and features call for attention when extrapolating our findings to the most recent generation. Massive online-resources, integrated social media and smarter technologies are engendering a new evolving digital ecology that has dramatically enhanced convenience and social connection. The new digital environment, however, is equally a mixture of commercial elements, biased information, and even more aggressive factors. It is of a necessity for policy-makers to balance both opportunities and risks together with ICT development. Regulatory challenges arise in framing people's digital life through strict guidelines or interventions as technological innovations are becoming more embedded in our daily life in a more rapid and take-for-granted way. As a consequence, it might be more useful to work through promoting relevant and updated literacy that extends IT skills. Future research might bring about more issue of ICT overload, and pay more attention to the significant heterogeneities of ICT use. Empirical work calls for more data that incorporates multiple platforms resources, which could also be more efficient with government's support.

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Glossary

ICT	Information Communication Technology
CAI	Computer Aided Instruction
CIA	Conditional Independence Assumption
PSM	Propensity Score Matching
HE	Higher Education
LSYPE	Longitudinal Study of Youth People in England
STEM	Science, Technology, Engineering, and Mathematics
MCS	Millennium Cohort Study
MMOG	Massive Multiplayer Online Games
SHARE	Survey of Health, Ageing and Retirement in Europe
PCA	Principal Component Analysis
CMP	Conditional Mixed Process
SEC	Social Economic Classification
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
NVQ	National Vocational Qualification
FSM	Free School Meal
BMI	Body Mass Index
SDQ	Strength and Difficulties Questionnaires
BAS	British Ability Scale
CPRS	Child-Parent Relationship Scale