New Technology in Schools: Is There a Payoff?

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Executive Summary

In recent years the role of investment in Information and Communication Technology (ICT) as an effective tool to raise educational standards has attracted growing attention from both policy makers and academic researchers. While the former tend to express enthusiastic claims about the use of new technologies in schools, the latter have raised concerns about the methodological validity of much of the research undertaken.

The view that ICT could help to raise educational standards dates back to the Fifties, and builds on some of the original findings by the Harvard psychologist Skinner (1954, 1958). More recently, support for the effectiveness of ICT as a teaching and learning device comes from the educational literature. Yet results are generally inferred from simple correlations between ICT and pupil performance, without taking full account of other factors (such as school characteristics, resources and quality) that may be related to both ICT resources and pupil outcomes. These methodological short-comings cast serious doubt on the validity of most of the existing research which finds a positive relationship between computers (and/or computer software) and student outcomes. In contrast, the small number of economic studies that address these issues by applying more rigorous methods of analysis, report no evidence for a positive impact of ICT on pupil outcomes.

In recent years, and in parallel with the widespread belief that new technologies account for much of the productivity resurgence in workplaces in the Nineties (see Jorgenson and Stiroh, 2000), the UK government has motivated its sizable ICT investment in schools by stressing the importance of ICT in raising educational standards and creating opportunities for every child. The positive rhetoric about ICT in the UK has been backed up by considerable government investment. Starting from 1997, the government has encouraged the widespread use of ICT for teaching and learning in schools: formal plans were set-up under the 'National Grid for Learning' in order to equip schools with ICT facilities and train teachers to make an effective use of ICT. Between 1998 and 2002, ICT expenditure in England almost doubled in secondary schools, and increased by over 300 percent in primary schools.

In this paper, we ask whether this considerable increase in ICT investment has made any difference to educational standards. More specifically, we evaluate whether

changes in ICT investment had any causal impact on changes in educational outcomes in English schools over the period from 1999 to 2003. To do this, we mainly rely on administrative data at the level of Local Education Authority. We also make use of detailed information contained in a survey about ICT use in English schools to help interpret our findings. To identify the *causal* impact of ICT use on pupil achievement, we exploit a policy change that occurred in 2001, using an Instrumental Variable (IV) approach. Specifically, we consider how a change in the rules governing ICT investment in different regions of England led to changes in ICT investment and subsequently changed educational outcomes. In our quasi-experimental setting, we identify the impact of ICT investment using the magnitude of the gain or loss experienced by different LEAs as a result of the change in the funding system. The results should be interpreted as the causal effect of ICT investment on educational outcomes for LEAs that were substantially affected by the change in the funding system over this particular time period (i.e. it is not the average effect of a change in ICT investment for the whole population of schools).

Unlike previous economic studies, we find evidence for a positive causal impact of ICT investment on educational performance in primary schools. This is most evident in the teaching of English, where we also show evidence that there is high use of ICT for teaching purposes. We also observe a positive impact for Science, though not for Mathematics. Hence, in this context, there is evidence of a causal link between a substantial increase in ICT investment and a rise in educational standards.

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1 Introduction

Among policymakers it is widely believed that Information and Communication Technology (ICT) investment has an important role to play in raising educational standards. The view that ICT can help raise educational standards dates back to the Fifties, and builds on some of the original findings by Skinner (1954, 1958), the Harvard psychologist who claimed that new technologies in schools could make learning dramatically more efficient. In more recent years, and in parallel with the widespread belief that new technologies account for much of the productivity resurgence in workplaces in the Nineties (see Jorgenson and Stiroh, 2000), there has been growing interest in the use of computers in the classroom.

In recent years the UK government has motivated its sizable ICT investment in schools by stressing the importance of ICT in raising standards and creating opportunities for every child; recently the Secretary of State for Education has spoken of ICT as 'crucial to our drive to raise standards'.[1] Also, it is envisaged that ICT should be used across the whole school curriculum. One government document supporting the use of ICT asserts that 'ICT can make a significant contribution to teaching and learning across all subjects and ages, inside and outside the curriculum' (DfES, 2003).

The positive rhetoric about ICT in the UK has been backed up by considerable government investment. In 1997, the Government announced its plans to encourage the widespread application of ICT in teaching and learning in maintained schools (Ofsted, 2001). Between 1998 and 2002, ICT expenditure in England almost doubled in secondary schools (from an average of about £40,100 per school to just under £75,300 or 3 percent of overall expenditure) and increased by over 300 percent in primary schools (from £3,600 in 1998 to £12,900 in 2002, or about 2 percent of overall expenditure).

Is this a good use of public money? Some support for the effectiveness of ICT as a teaching and learning device comes from both the educational literature and psychological research. Yet a recent review by Kirkpatrick and Cuban (1998) suggests that evidence for the effectiveness of ICT in schools is both limited and mixed. Most importantly, results are generally inferred from a positive correlation

[1] Ruth Kelly, Speech to BETT, the annual educational technology show, London 2005.

between ICT and pupil performance, without taking full account of other factors (such as school characteristics, resources and quality) that may be related to both ICT resources and pupil outcomes. This gives rise to serious concerns about the validity of findings from such studies. Starting with the study by Angrist and Lavy (2002), there have been a small number of economic studies that address this issue and apply more rigorous methods of analysis: none of them, with exception of Banerjee et al. (2004) on schools in Indian urban slums, shows evidence of a positive causal relationship between computers (and/or computer software) and pupil performance. Thus, economists tend to take the opposite view to policy makers with respect to the efficacy of ICT investment.

In this paper, we evaluate whether changes in ICT investment have had any impact on changes in educational outcomes in English schools. To do so, we mainly rely on administrative data (at the level of Local Education Authority) over the period from 1999 to 2003. To deal with potential endogeneity problems relating to ICT use and pupil achievement, we exploit a policy change that occurred in 2001 from which we devise an Instrumental Variable strategy to identify the causal impact of ICT expenditure. Specifically, we consider how a change in the rules governing ICT investment in different regions of England led to changes in ICT investment and subsequently changed educational outcomes. Our approach therefore identifies the effect of being a 'winner' or a 'loser' in the new system of ICT allocation to schools. Finally, we draw on insights from a school survey about ICT use in English schools. Unlike previous studies in the literature, we find evidence for a positive causal impact of ICT investment on educational performance in primary schools. This is most evident in the teaching of English, where we also show evidence that there is high use of ICT for teaching purposes.

Our paper is structured as follows. We start in Section 2 with a brief review of the economic literature on computers and education. Then in Section 3, we discuss how ICT (i.e. mainly computers) is used in English schools and describe the changing policy context. In Section 4, we present an outline of the analytical framework before discussing results in Section 5. We draw together our conclusions in Section 6.

2 Literature on the Effect of Computers in Schools

As discussed by Angrist and Lavy (2002), the educational use of computers generally falls under two broad headings: computer skills training, which teaches students how to use computers, and Computer-Aided Instruction (CAI), which uses computers to teach things that may or may not have any relation to technology. While basic familiarity with the former seems undeniably useful, the role of CAI is controversial. The theoretical case for CAI is not well developed and there are reasons to think computers in the classroom may be a distraction and displace other, more effective, teaching techniques.

Some empirical support for the effectiveness of CAI comes from both the educational and psychological literature. There are many qualitative studies which summarize the overall impression of people participating in CAI demonstration programs; many others attempt some quantitative analysis, but often do not have a suitable comparison group of non-CAI users. A recent review of the international evidence is provided in Kirkpatrick and Cuban (1998). The authors conclude that the evidence for the effectiveness of ICT in schools is limited and mixed. They also cast some doubt on the methodological approach of existing studies.

Evidence for the English experience in recent years is mainly reported in Becta (2002), Ofsted (2001) and in other government reports. According to Ofsted (2001) 'there is evidence of a link between high standards across the curriculum and ICT use in schools'. Similarly, Becta (2002) concludes that 'differences in attainment associated with greater ICT use were clearly present in National Tests or GCSEs'.[2] Unfortunately, as for most of the studies reviewed by Kirkpatrick and Cuban (1998), results are generally inferred from a positive correlation between ICT and pupil performance. However, the use of computer and teaching software may well be correlated with other inputs to education which are unobserved or imperfectly measured. Neglecting factors that contemporaneously affect performance and technology may lead to biased estimates of the influence of CAI on pupil achievement. This gives rise to serious concern about the validity of findings.

This problem is well illustrated in the recent study by Fuchs and Woessman (2004), which uses international data from the Programme for International Student

[2] GCSE is General Certificate of Secondary Education, the exams taken in the final year of compulsory schooling at age 15/16.

Assessment (PISA). They show that while the bivariate correlation between the availability of computers at school and school performance is strongly and significantly positive, the correlation becomes small and insignificant when other school characteristics are taken into account. However, as they acknowledge, their estimates do not necessarily show the causal effect of computers on pupil performance if there are other important omitted variables. Establishing whether computers have a causal impact requires experimental or quasi-experimental evidence, where a 'treatment' and 'control' group can be properly defined.

Angrist and Lavy (2002) is the first such study in this vein. They use the fact that the Israeli State lottery funded a large-scale computerization effort in many elementary and middle schools to facilitate a controlled comparison between schools that received funding and schools that did not receive funding. They find no evidence that increased educational use of computers raised pupil test scores. In fact, with regard to 4th grade Maths scores, they find a consistently negative and marginally significant relationship between the programme-induced use of computers and the outcome measure.

Leuven *et al.* (2004) also use a government scheme - this time in The Netherlands - to evaluate the effect of computers (and software) on pupil outcomes in a quasi-experimental setting. They find that the extra funds for computers and software do not have a positive impact on pupils' achievement, and even seem to have a negative effect on language and Maths scores. From a survey of schools, the authors infer that funding was not used to purchase computer hardware (where needs seem to have been satisfied), but to buy new software or invest in Internet connections. Similarly to Angrist and Lavy (2002), they conclude that instruction methods using computers may be less effective than other instruction methods.

Goolsbee and Guryan (2002) analyze the effect of a program in the US to subsidize schools' investment in Internet and communications. They do not have a quasi-experimental setting, but they try to isolate the program's effect from underlying trends by exploiting a threefold strategy: first, they exploit cross-sectional variation in the subsidy rate across schools in the same time period; secondly, they look at growth rates rather than at levels; and thirdly, they include a detailed set of controls in their analysis. Although the program led to an increase in Internet connections, they find no impact on any measure of pupil achievement.

Rouse *et al.* (2004) present results from a randomized study of a popular instructional computer program designed to improve language and reading skills in the US. Their estimates suggest that while the use of computer programs may improve some aspects of students' language skills, these gains do not translate into a broader measure of language acquisition or into actual reading skills. The authors argue that their study is a strong test of the educational benefit of computer software since the program they evaluate (FastForWord) is on the leading edge of scientifically-based computer technology in schools and one of the more expensive programs available.

An important exception to the body of work that reports no effects is Banerjee et al. (2004). Their analysis is in a very different setting and presents the results of a randomized policy evaluation administered in Mumbai and Vadodara (India), aimed to improve the quality of education in urban slums. The authors find that a computer assisted program, designed to reinforce mathematical skills, had a large and positive impact on math scores; but the program did not produce positive spillovers to other subjects. Although these results can hardly be compared to findings from other studies based on developed countries, the authors are the first to show (in a causal sense) that CAI may have the potential to help disadvantaged children improving their educational achievements.

In summary, the small number of studies to date that address the 'endogeneity' issue find little evidence of a positive relationship between the use of computers and/or computer software and educational performance. In some cases there may even be a negative relationship. The main conclusion is therefore that the use of CAI in schools to teach language and mathematical skills is not effective on average (and certainly not cost-effective); in fact, it may be inferior to teaching methods that are being replaced by technology. If this is true, then the policy emphasis on using ICT to teach subjects across the curriculum is misplaced and it would be better to divert investment from ICT into an aspect of education where there is evidence of positive returns. In the remainder of this paper, we consider these important, policy relevant issues for the English school system.

3 ICT in English Schools

In 1997 the UK government announced plans to encourage the widespread application of Information and Communication Technology (ICT) to teaching and learning in maintained schools.[3] The intention was to equip schools with modern ICT facilities; create a National Grid for Learning (NGfL) containing educational information and study material; and organize a program of in-service training for teachers and school librarians to enable them to make effective use of ICT in their professional work (Ofsted, 2001). A target for the computer-pupil ratio was set, where the aim was to achieve a target of 1:8 in primary schools and 1:5 in secondary schools by 2004.

Throughout this period, funds were distributed to schools through their Local Education Authorities (LEAs).[4] Between 1998/99 and 2000/01, the main government funding was channeled to LEAs through an 'Infrastructure and Services' grant (also known as the NGfL grant). From 2000/01 onwards, there was an extra component (about 16-20 percent of the total) aimed at connecting schools to Broadband. The increase in the funding over time was considerable, rising from £102 million in 1998/99 to £349 million in 2002/03. Trends over time are shown in Figure 1, which shows average ICT funding (upper panel) and ICT funding per pupil (lower panel) for LEAs. The Figure displays a dramatic increase in resources from 2000 onwards (i.e. the Financial Year 1999/2000).

Using information from the 'ICT Survey of Schools in England', we show how this translated into ICT use in schools in 2000 and 2003.[5] The Survey is an annual assessment of schools in England, where about 25 percent of secondary schools and about 6 percent of primary schools are surveyed about ICT use and funding. Although schools participating in the survey constitute a representative sample of English schools in terms of key characteristics,[6] ICT expenditure per pupil

[3] Maintained schools refer to all non-private sector schools in the UK; these are funded by Local Education Authorities, largely from central government grants.

[4] There are 150 Local Education Authorities in England. They are responsible for the strategic management of local authority education services including planning the supply of school places, ensuring that every child has access to a suitable school place, intervening where a school is failing its pupils and for allocating funding to schools.

[5] We adopt the convention that the school or financial year 1999-2000 is known as '2000' (to correspond to the time at which examinations take place). The school year starts in September whereas the Financial Year starts in April. The difference in timing should not be a problem as it is unlikely that spending between April and June would affect pupil performance in summer examinations (May/June).

[6] We have checked the representativeness of schools in the Survey in terms of size, pupil characteristics, pupil/teacher ratio and student achievement.

is higher on average than the LEA figures would suggest. For example, in 2003, primary and secondary schools spent £56 per pupil and £68 per pupil respectively. In contrast, specific ICT funding per pupil (shown in Figure 1) was £47 per pupil at this time. The main reason for this difference is that schools may also use general school funding (i.e. non-ICT specific) for their ICT expenditure. In fact, in the ICT survey for 2000 and 2002, schools were asked how much of their ICT expenditure came from the source of funding shown in Figure 1. On average, for primary and secondary schools, this was about 20 and 12 per cent respectively in 2000; these shares went up to 45 and 29 per cent in 2002.[7] This shows that ICT-specific funding has become more important as a source of school-level ICT expenditure in recent years (especially for primary schools). Also, schools in the ICT survey were already well resourced in terms of ICT in 2000, before the major increase in ICT-specific investment. For example, the computer/pupil ratio is quite close to the (2004) government target in 2000 at 1:10 in primary schools and 1:7 in secondary schools.

Nevertheless, for the schools in the sample, Table 1 shows quite sizeable changes over a relatively short period. By 2003, the computer/pupil ratio was 1:6 in primary schools and 1:4 in secondary schools. All the indicators of ICT use in the classroom show fairly high percentage increases in this short time period – this includes: ICT expenditure per pupil; the computer/pupil ratio; the percentage of teachers using ICT regularly in their teaching; the percentage of teachers trained to use ICT (and those who have recently updated their training). For both primary and secondary schools, internet coverage was universal in 2003 (from a high base in 2000). Although secondary schools were better equipped with ICT in 2000, the greatest relative increase over time was experienced in primary schools. Also, it is notable that ICT is used regularly for teaching purposes in a much higher percentage of primary schools than secondary schools: in 2003, ICT was reported to be used regularly for teaching in 92 per cent of primary schools, as compared to 55 per cent of secondary schools.[8] Hence, one might expect any effect of 'computer-aided

[7] For 2000 and 2002, we have checked whether ICT expenditure per pupil coming from ICT-specific funding is consistent in the school surveys with what the administrative data suggests (net of funding for Broadband connectivity, which does not go directly to schools). We find that schools in the ICT survey report a lower allocation from this source than what we might expect. This may be due to reporting errors by schools or retention of resources at LEA level to fund coordinated activities (such as training). However, the rise in ICT expenditure from 'ICT specific' funding is broadly consistent at the school and LEA level, being above 200% between 2000 and 2003.

[8] This is based on the following two questions: 'How many teaching staff are employed in the school at present?'; 'How many teaching staff use computers on a regular basis?'

instruction' on educational performance to be more evident in primary schools than in secondary schools.

In Table 2, we show the share of ICT expenditure spent on various items in 2000 and 2002 (the only years where this question was asked). It is interesting to note that the share of ICT expenditure devoted to hardware and software decreased by 14 and 3 per cent in primary and secondary schools respectively whereas the share of resources devoted to teacher training rose by 57 per cent for primary schools and by 50 per cent for secondary schools. This suggests that the extra funding may have improved the quality of ICT use in schools (through teacher training) rather than simply increase the amount of ICT equipment.

Figure 2 provides additional information about the use of ICT in schools. Specifically, it depicts the proportion of schools where ICT is 'substantially used' in the teaching of particular subjects for a pooled sample of schools in the ICT Survey between 2000 and 2003 (when this question was asked). For any particular subject, ICT is used 'substantially' in at least 20 per cent of schools at both primary and secondary level (except for some subjects in primary school, such as music, design and foreign languages - which may not be taught in all primary schools or at least not very formally). The non-ICT subject where ICT is most often used according to this categorization is design in secondary school, and then English at primary school. About 65 percent of primary schools report that they 'substantially use' ICT in the teaching of English. The next most important 'ICT user' is Maths (followed by Science), where ICT is 'substantially used' in about 56 percent of primary schools and 40 percent of secondary schools. Thus, a relevant question is whether all this intensive use of computers as an instructional method has an observable impact on pupils' educational outcomes.

3.1 The ICT funding mechanism

Government grants for ICT funding are distributed to schools via their Local Education Authorities (LEAs). To obtain this source of funding, LEAs must agree to match any ICT-specific funding with general education funding (also provided by central government - but not ring-fenced for ICT). Hence, to some extent, school-level funding for ICT depends on the importance attached to ICT by the LEA. The administrative data for ICT funding (as shown in Figure 1) reflects both components of the ICT grant.

In the years 1999 and 2000, funding for ICT was allocated to LEAs through a bidding process. Anecdotal evidence from the Department for Education and Skills suggests that the aim was to direct money towards LEAs that were proposing innovative and interesting ways to manage the roll-out of the government programme discussed above. Almost all LEAs received ICT funding, but its level was related to the degree of interest in their proposal. From 2001 onwards, there was an important change in the allocation mechanism - the rationale being to make the system more equitable. From then on, allocations were made according to a formula based on school and pupil numbers in LEAs. For a component of the grant (i.e. that relating to Broadband connectivity), there was also an adjustment made for population density.

The change in the allocation mechanism created winners and losers among LEAs. LEAs which had benefited a lot under the old system stood to lose from the transition to a formula-based system, and vice versa. In Figure 3, we plot the log share of total ICT funding received by each LEA before and after the policy change. We also plot the corresponding 'fitted share' of ICT funding, which is based on pupil numbers, school numbers and population density in the LEA. After the policy change the correspondence between the actual and fitted share is close. Before the policy change, there is considerable divergence between the actual and fitted share - showing that allocations to LEAs were not made on the same basis before and after the policy change.[9] Hence some LEAs gained from the new system, whereas others lost - and the magnitude of the gain or loss can be estimated by the difference between the share of funding received by the LEA in the new system relative to the share of funding it received in the old system.

The key features of the policy change that are important for the analysis are as follows: the basis for the funding allocation was different in the new system and the old system; the change created 'winners' and 'losers'; the change was not pre-empted by LEAs in how they were bidding for funding the year before the rule change (this seems very unlikely. Furthermore, the funding share in the two pre-change years, 1999 and 2000, is very highly correlated). In our analysis, we use the magnitude of gain or loss as a result of the change in system, combined with the timing of the change, to predict changes in ICT funding at LEA level. We argue that this provides

[9] There is very little change over this time period between LEAs with respect to components of the formula (school and pupil numbers). So, the observed differences between fitted and actual shares in 2000 and 2001 do not reflect major changes in the characteristics of LEAs. They effectively capture the shift in the allocation of ICT funds induced by the new allocation system.

an exogenous source of variation in ICT funding that can be used to analyze the relationship between ICT investment and educational outcomes, thus overcoming potential endogeneity problems.

A further illustration of the effect of the rule change in 2001 can be seen in Figure 4, which shows trends in ICT funding per pupil (indexed at 1 in 1999) over time for two groups of LEAs: those which were at or below the 25th percentile of the ICT expenditure per pupil distribution in 1999; and those which were at or above the 75th percentile. The consequence of the rule change in 2001 was that these two groups became much closer in terms of per pupil ICT funding from that time onwards. Among these two groups, the relative 'winners' were those LEAs at the lower part of the distribution in 1999 and 2000.

In Tables 3 and 4, we also use the ICT school survey to examine how schools in these two categories of LEAs fared between 2000 and 2003, in terms of their ICT inputs. Table 3 shows statistics for primary schools. In terms of ICT expenditure per pupil and the computer-pupil ratio, primary schools in 'top LEAs' (i.e. those at or above the 75th percentile of the distribution in 1999) do not look different from those in 'bottom LEAs' (i.e. those at or below the 25th percentile of the distribution in 1999). However, as would be expected from the large relative increase in government funding to the latter LEAs, the rate of increase in most school-level indicators is considerably higher in 'bottom LEAs' than in 'top LEAs'. This pattern is far less clear for secondary schools (in Table 4). The rate of increase in ICT expenditure per pupil is only slightly higher for schools in 'bottom LEAs' relative to 'top LEAs' and the rate of increase in the computer-pupil ratio is lower in 'bottom LEAs'. This may reflect the fact (discussed above) that for secondary schools ICT expenditure per pupil has not increased over time as much as in primary schools and ring-fenced ICT funding appears to be less important as a source of overall ICT expenditure.[10]

4 Analytical Framework and Identification

The key issue is to identify the relationship between ICT investment and educational outcomes, while taking account of any other confounding factors. To overcome the

[10] There are no rules for how LEAs allocate ICT funding to schools: 'they have the freedom to manage allocations at a local level in order to meet local priorities' (DfES, 2004).

endogeneity problem, we make use of the quasi-experimental setting provided by the change in the funding allocation mechanism to implement an Instrumental Variable Strategy.

Because our identification strategy is based on a rule change at LEA level, we rely on data at this level of aggregation. We construct an LEA-level panel using administrative data over the 1999-2003 period.[11] Information includes ICT funding; pupil performance; other LEA funding to schools; and LEA characteristics, such as the number of schools and pupils. We know that the rule change created 'winners' and 'losers' among LEAs, and that the magnitude of gain or loss can be estimated from the difference between the share in overall expenditure received by the LEA in the year prior to the policy change and the share after the policy change.[12] Hence, our first-stage regression is based on the following key relationship:

$$\Delta C_{it} = \lambda Index_{it\geq 2001} + \xi_i + \phi_t + \theta \Delta X_{it} + \omega_{it} \qquad (1)$$

where ΔC_{it} is the change in log(ICT funding per pupil) for LEA i in time t; $Index_{it\geq 2001}$ is a measure of 'gain' or 'loss' incurred by LEA i as a consequence of the change in the allocation mechanism in the years after the change ($t\geq 2001$); ξ_i is an LEA fixed effect potentially capturing its relative position in the ICT funding distribution, before the policy change; ϕ_t is a set of year fixed effects; ΔX_{it} is a vector of changes in inputs (in logs) expected to affect ICT funding per pupil at the LEA-level; and ω_{it} is an error term.

Our second stage regression can be written as follows:

$$\Delta Y_{it} = \beta \Delta C_{it} + \alpha_i + \delta_t + \gamma \Delta X_{it} + \varepsilon_{it} \qquad (2)$$

where ΔY_{it} is the change in pupil outcomes (in logs) in LEA i at time t; α_i and δ_t are LEA and year effects respectively; ΔX_{it} is the same vector of changes in other inputs expected to affect pupil outcomes at the LEA-level; and ε_{it} is an error term.

Controlling for LEA effects (ξ_i and α_i) is potentially important in our analysis as being a 'winner' or a 'loser' from the rule allocation change (reflected

[11] There are also various data constraints at school-level - for example, we need to rely on retrospective information to construct the change in the computer/pupil ratio for schools. We do not have retrospective information on ICT expenditure per pupil. The school-level surveys are based on a repeated cross-section, where relatively few have been sampled more than once.

[12] It does not make much difference whether we use 1999 or 2000 data to calculate the share of ICT funding allocated to a particular LEA. There is a strong correlation between the shares allocated to LEAs in both these years.

in $Index_i$ itself) may be correlated with other LEA-specific characteristics, which are in turn correlated with both computer funding and pupil outcomes. This might happen if LEAs that were particularly good at extracting ICT funds in the bidding process (i.e. pre-policy) for educational purposes were also good for their schools in other ways. Crucially, it is $Index_i$ interacted with a dummy for the period in which the policy is in place *Policy-on* (i.e. for the post-change years, $Index_{it \geq 2001}$) that is used for identification, and not $Index_i$ itself. We therefore control for LEA effects in our IV strategy using $Index_i$ as a regressor in both the first and second stage of the regression.[13] Our identification strategy is similar to the non-linear IV approach followed by Angrist and Lavy (2002).[14]

One might ask whether instrumenting for the change in ICT funding is really necessary when estimating regressions at LEA level. For example, there is exogenous variation in the growth of ICT funding as this is largely determined by central government. Furthermore, with such aggregate data, unobserved attributes of pupils or schools that are correlated with the growth of ICT funding and with educational outcomes may not be so important. There are two main reasons for an IV approach in this context. Firstly, the measure of ICT funding is only a proxy for ICT investment at school-level. In Section 3, we have described how ICT-specific funding is just a fraction of overall ICT expenditure in schools. The fact that we may be measuring changes in the true ICT input with error could lead to downward bias in our estimate of the effect of ICT investment on educational outcomes.[15]

Secondly, because LEAs must provide matched funding to 'ICT-specific' funding, the level of LEA funding (and relevant school expenditure) will reflect the extent to which LEAs prioritize ICT as a source of funding. This adds a further non-random dimension to ICT funding observed at LEA level, which may be correlated with educational outcomes. If LEA priorities change over time, this effect will not be removed with the inclusion of LEA fixed effects. In Table A1 of the Appendix, we

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[13] We also experimented with more flexible and non-parametric alternatives. First, a full battery of LEA dummies (fixed effects) was used in both stages. When this was done, the same point estimates were obtained, although standard errors were slightly larger; yet, this only marginally affected the significance of the estimated coefficient. Alternatively, we included polynomials (up to the fourth power) of $Index_i$; point estimates and the significance of our results were fully confirmed.

[14] In their study, schools applying for ICT grants are ranked within city, and actual funding is a non-linear and non-monotonic function of the rank. This relation forms the basis for an Instrumental Variable approach, which is valid when controlling for parametric functions of the rank itself.

[15] Ashenfelter and Krueger (1994) show that this problem is exacerbated in a panel context.

show some evidence that ICT funding is 'crowding out' other types of LEA funding, since there is a negative relationship between ICT funding per pupil and other LEA funding per pupil. However the instrument used in our regressions is completely unrelated to non-ICT funding per pupil at the LEA level.

There is therefore a strong rationale for instrumenting the change in ICT funding, even when analyzing relationships at the LEA level. We then identify an average causal response (ACR) of educational achievement to changes in the funding mechanism. The ACR is defined by Angrist and Imbens (1995) and is a generalization of the local average treatment effect (LATE) when the treatment is not binary. In our case, the treatment intensity varies between LEAs, and is proportional to the losses or gains experienced by LEAs as a result of the change in the funding mechanism. Therefore, ACR will depend on the distribution of treatment intensities across LEAs: big 'losers' or big 'winners' from the change in system will have a disproportionate effect on the IV estimate. We will return to this point later, when discussing the interpretation of our findings.

5 Results

5.1 First stage regressions

Regressions are based on administrative data at LEA level for the years 1999-2003. All variables are specified in log changes, except for $Index_i$, its interaction with the timing of the policy change, *Index*Policy-on* (i.e., $Index_{it\geq 2001}$), and a sparsity factor (constant over time). The first stage regression is shown in Table 5. In column 1, we show the relationship between the instrument and the change in ICT funding per pupil controlling for $Index_i$. Then in column 2, we also include controls for variables used to allocate ICT funds to LEAs in the post-reform period (sparsity; pupil numbers; school numbers) and controls for the pupil-teacher ratio and non-ICT funding per pupil, as well as a set of year dummies. The key parameter of interest is the estimated coefficient on *Index*Policy-on*, which is positive and highly significant in both specifications. The reported F statistics are well above the critical values suggested in Staiger and Stock (1997) to detect weak instruments; also, the marginal R-squared for the excluded instrument suggests *Index*Policy-on* can account for a large proportion of the variation observed in the growth rate of ICT after the policy change.[16] Finally, an interpretation of the coefficient is that if the rule change led to an increase of about 10 percent in the relative share of ICT funding received by an LEA, this would mean a 9 percentage point increase in ICT funding per pupil within that LEA.

Although our identification strategy exploits the interaction *Index*Policy-on* and the exogeneity of the date of the policy change, we also test for the balancing properties of $Index_i$ itself; this provides additional information about the validity of our identification strategy. To do so, we study whether there is any relation between a number of observable characteristics of LEAs before the period under analysis and $Index_i$. Results from this exercise are reported in Table A2 (in the Appendix to this paper), where we show simple correlations and regression results. If the changes in the allocation of ICT expenditure induced by policy reform are independent of long-run LEA trends and characteristics, we expect to find little relation. This is clearly the case, as shown in Table A2, and thus provides additional evidence as to the validity of our strategy.

In Table 6, we estimate similar specifications at the school-level since it is important to know whether the instrument has some power at this level, and to see whether the impact is different for primary schools than for secondary schools. In this case, the dependent variable is the computer-pupil ratio and is based on retrospective data in the ICT Survey (where schools are asked about the number of computers used for teaching at the present time and three years previously; similar questions are not asked about ICT expenditure). Some additional school-level controls are included (percentage of students eligible for free school meals; percentage of students with Special Educational Needs). The instrument is positive and significant for primary schools in both specifications, though much less powerful than in regressions specified at the LEA level.[17] In this case, a 10 percent increase in the share of ICT funding received by an LEA leads to an increase in the computer-pupil ratio of about 0.13 percentage points.[18] In contrast, the estimated coefficient is zero when estimating

[16] Notice that we only have one exclusion restriction and, since the level of variation in the dependent variable and in the excluded instrument is the same, the F statistic is asymptotically equivalent to the square of the t statistic on *Index*Policy-on*.

[17] In this specification, the dependent variable varies at the school level, while the instrument is fixed within LEAs. As a result, the F statistic is *not* asymptotically equivalent to the square of the t statistic on *Index*Policy-on*. This helps in explaining the much weaker explanatory power of our exclusion restriction in the school level models as compared to the LEA models reported earlier.

[18] The estimated coefficient at the school level is very different to that at the LEA level. Apart from the fact that the measure of ICT is different, there are a number of possible reasons for this: schools only

the regression for secondary schools. Given the discussion in Section 3, it is not surprising to see that the IV strategy has no power in this case. Hence, in the second stage of our analysis, we focus exclusively on primary school outcomes.

5.2 The effect of ICT funding on educational outcomes

In England, compulsory education is organized into 4 Key Stages (1-4) and national tests (which are externally set and marked) are taken at the end of each Key Stage for pupils of age 7, 11, 14 and 16 respectively. The test at age 11 is taken at the end of primary school (Key Stage 2). Marks for each test are converted into a level on a scale of 2-6, where 'level 4' is the standard deemed appropriate at this stage of education. The educational knowledge and skills required at each level are set out in the National Curriculum. Government targets for pupils of age 11 are based around the percentage of pupils that attain 'level 4'. Hence, this is the measure of performance recorded in the School Performance Tables and used in our analysis (at LEA level).

In Tables 7 to 9, we report results from LEA-level regressions, where the outcome variables measure examination performance at age 11 in English, Maths and Science respectively. [19] Table 7 shows three specifications where the dependent variable is the proportion of students attaining level 4 or above in English at Key Stage 2. In column 1, we show the OLS results. In columns 2 and 3 we show results from IV regressions, controlling for $Index_i$ (column 1) and then adding all other controls (column 2). The OLS regression shows no relationship between ICT funding per pupil and performance in English. In contrast, the IV regressions show a positive and significant relationship between ICT funding per pupil and performance in English, which is not sensitive to whether controls are included. The coefficient shows that a doubling of ICT funding per pupil in schools led to a 2 percentage point increase in the proportion of pupils achieving level 4 or above in English at age 11. As discussed above, changes in ICT funding of this magnitude really did happen for primary schools over this period and the impact on performance in English is notable given that the average growth rate of pupils' scores in this subject was around 7 percent between 1999 and 2003. However, the causal effect of ICT identified here is

partly rely on ICT-specific (i.e. NGfL) funding for ICT-related expenditure; only a fraction of ICT expenditure is used to buy computers; the LEA may use ICT-specific funding to finance joint activities (e.g. teacher training); the change in computers per pupil is computed over two periods, while our instrument is mainly capturing changes occurring between 2000 and 2001.

[19] For school-level regressions, the instrument is much weaker in the first stage. Hence IV estimates are very imprecisely determined in the school-level regressions.

not the average population effect (i.e. for all schools in England) but rather the causal effect of large changes in ICT investment for LEAs that were substantially affected by the rule change.[20]

In Table 8, similar regressions are shown, where performance in Mathematics is the dependent variable. In this case, the relationship between ICT funding per pupil and the measure of performance is positive, but insignificant, with the estimated coefficients being less than half the size of the estimated effect for English. Finally, in Table 9, results show no relationship between ICT funding and performance in Science for the OLS regressions. However, the coefficient is positive and significant in the IV regressions. In this case, a doubling of ICT funding per pupil leads to an increase of 1.4 percentage points in the proportion of pupils achieving level 4 or above.

5.3 Robustness

Some issues remain to be discussed. First, as shown in the Figures discussed earlier, our IV strategy is more binding for the years immediately before and after the change in the rules for the allocation of ICT funds. An important question is therefore: how are results affected if we apply the IV strategy to the model in Equation (1) over the years 1999-2000 and 2000-2001 only? Secondly, although the policy change profoundly altered the distribution of ICT funding between 2000 and 2001, it might have taken some time to gain full impact; it is therefore important to determine whether the impact of ICT on educational achievement grew over time, after the policy change.

We address these points in Table 10. The first row reports the impact of ICT on educational achievement, when only the 1999-2000 and 2000-2001 window is considered; the second and third rows respectively report results comparing 1999-2000 to 2001-2002, and 1999-2000 to 2002-2003, thus allowing the policy to take some time to produce its full effect.

Results for English are reported in the first column. We find a positive and significant effect of ICT, even when we confine our attention to the immediate aftermath of the policy change: the estimated impact is 0.013, and significant at the 1 percent level. Also, the comparison of 1999-2000 with subsequent periods (2001-

[20] As described above, we identify the Average Causal Response. This gives more weight to LEAs that were substantially affected by the rule change.

2002 and 2002-2003) suggests the policy change took some time to produce its full effect.

As for Science, the estimated impact over 1999-2000 and 2000-2001 is significantly reduced; in fact, the IV estimates in Table 9 mainly capture an effect of the policy emerging in the period 2002-2003, which is estimated to be as large as that for English. Finally, we still do not find any positive impact of ICT on Maths scores.

5.4 Interpretation of the findings

Evidence discussed so far suggests that, in the English context, where the policy change in 2001 induced *large* changes in the ICT funding received by primary schools, ICT expenditure has led to significant improvements in school performance in English and Science tests at age 11, though not for Maths. How can we reconcile our evidence with previous studies in the field that find no effect?

The IV estimates presented in this paper identify the average causal response (ACR) of educational achievement to changes in the funding mechanism. ACR is a generalization of the Local Average Treatment Effect (LATE) when the treatment is not binary (see Angrist and Imbens, 1995), and depends on the distribution of treatment intensities across LEAs, with big `losers' or big `winners' disproportionately affecting the IV estimates. In fact, we know that for big 'winners', defined as those LEAs in the top quartile of our $Index_i$ distribution, the average growth rate of ICT funds was roughly 60 percent after the policy change (i.e. over 2001-2003); this contrast with a much smaller change of 20 percent for big 'losers', i.e. LEAs in the bottom quartile of the $Index_i$ distribution (see Figure 4). Intuitively, it is the comparison between these two groups, and the associated change in the allocation of ICT funds, that drives identification of the impact of ICT on educational outcomes.

To further illustrate this interpretation, we implement the method developed in Angrist and Imbens (1995), which allows identification of those LEAs that contributed most to the estimates of the ACR, in terms of acceleration in their ICT funding. To keep it as simple as possible, we make use of a binary version of our instrument; this takes the value one when $Index_i$ is positive or zero (i.e. for ‘winners’), and the value zero when $Index_i$ is negative (i.e. for ‘losers’). Our IV results are fully confirmed when this version of the instrument is used, with the impact of ICT expenditure on Science rising to above 0.20.[21]

ACR estimates should be interpreted as the *weighted average* impact of a 1 percent change in the growth rate of ICT funding, for LEAs affected by the policy change; for each level of the growth rate of ICT funding, say *j*, the *weighting* function is proportional to the fraction of LEAs that went from ICT funding below *j* to ICT funding above this level, as a result of the policy change. So, which LEAs are *weighted* more in our ACR estimates?

A simple and informative answer can be provided graphically, analyzing the cumulative distribution functions (CDFs) of the growth rate of ICT separately for winners and losers (as defined by whether *Index* is positive or negative), after the policy change; computations are carried out over the common support of the ICT funding.[22] Results are depicted in the top panel of Figure 5.[23] The difference between the two CDFs, at each point *j* of the ICT funding distribution, is a function capturing the contribution (i.e. the weight) of that point to the ACR estimate; this is plotted in the bottom panel of Figure 5, with associated standard errors.

The graph indicates that LEAs significantly contributing to the ACR are those with growth rates of ICT expenditure between 50 percent and 70 percent, and up to 80 percent. For example, around 8 percent of the LEAs obtained 65 percent growth rates of ICT funding in the years after the policy change, whereas they would have obtained less in the absence of the shift; similarly, about 5 percent of the LEAs experienced a growth of between 75 and 80 percent in ICT funding as a result of the introduction of the new policy. These are the observations that contributed most to the estimation of the ACR discussed above, suggesting that our IV strategy mainly captures the impact of large changes in ICT investment on primary school performance.

[21] Yet the estimates based on a continuous version of $Index_i$ come from our preferred specification. In fact, a continuous measure of winners and losers is much better designed to control for LEA characteristics, which may spuriously affect the relationship between school performance and ICT funding.

[22] As a result, part of the bottom tail of the distribution for losers, and of the top tail of the distribution for winners, are trimmed out of the sample.

[23] Note that the fact that we observe no significant crossing of the CDFs also speaks in favour of the monotonicity assumption required for our strategy to identify a causal impact of ICT on educational outcomes.

6 Conclusion

It is difficult to establish the causal relationship between computers and educational outcomes because of the ‘endogeneity’ problem. There are only a small number of studies in the economic literature which attempt to address this issue. With the exception of the rather different Banerjee et al. (2004) paper on schools in Indian urban slums, they all find no evidence of a positive relationship between computers (and computer related inputs) and educational performance. In this study, we examine the issue in an English context, where there has been a major increase in information communication technology (ICT) investment since 1998.

We examine the relationship between changes in ICT investment and changes in educational performance in Local Education Authorities (LEAs). We overcome the ‘endogeneity’ problem by making use of a change in the rules about how ICT funds were allocated to different LEAs. Hence, we follow studies that use a quasi-experimental setting to estimate the effect of a given treatment status. In this case, the ‘treatment’ is measured continuously and reflects the magnitude of the gain or loss experienced by different LEAs as a result of the change in the funding system. In contrast with most previous studies in the economic literature, we find evidence for a positive impact of ICT investment on educational performance in primary schools. A positive effect is observed for English and Science, though not for Mathematics. Hence it seems that, in a context where there was a significant expansion of ICT investment, one can uncover evidence of an improvement in pupil achievement linked to ICT. This provides an interesting parallel, both to the existing work that does not find beneficial effects for pupils and to the related work on firms where there is evidence that ICT investment enhances firm productivity.

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Table 1 Trends in ICT Expenditure and Use of ICT resources; *Primary* and *Secondary* Schools.

	Primary Schools			Secondary Schools			
	99/00	02/03	% Change	99/00	02/03	% Change	Prim.-Sec., 99/00-02/03
ICT Expenditure per Pupil (£)	41	56	*+37*	60	68	*+13*	+24
Computers per Pupil	0.10	0.16	*+60*	0.15	0.23	*+53*	+7
% Using ICT Regularly	75	92	*+23*	38	55	*+45*	-22
% Trained to Use ICT	81	95	*+17*	75	83	*+11*	+6
% Recently Updated Training	57	85	*+49*	48	69	*+44*	+5
% Schools Connected to Internet	86	100	*+16*	99	100	*+1*	+15

Notes: Outlier schools have been excluded (schools in the top or bottom 1% of the distribution of either computers per pupil or expenditure per pupil). Number of primary schools: 627 in 1999/2000; 810 in 2002/2003. Number of secondary schools: 616 in 1999/2000; 714 in 2002/2003.

Table 2 How was ICT money spent in schools? Percentage devoted to different items.

		Primary Schools	
	1999/2000	2001/2002	% Change
Hardware	63	53	*-16*
Software	10	10	*+0.0*
Internet + TLC	8	7	*-12*
Training	7	11	*+57*
Technical Support	9	13	*+44*
Administration + Other	3	6	*+100*
		Secondary Schools	
	1999/2000	2001/2002	% Change
Hardware	57	55	*-3.5*
Software	9	9	*+0.0*
Internet + TLC	4	3	*-25*
Training	4	6	*+50*
Technical Support	14	17	*+21*
Administration + Other	12	10	*-17*

Table 3 Expenditure and Use of ICT resources, before and after the policy; 'top LEAs' vs. 'bottom LEAs', *Primary Schools*

	Primary Schools						
	Top LEAs			Bottom LEAs			
	99/00	02/03	% Change	99/00	02/03	% Change	Bottom-Top, 99/00-02/03
ICT Expenditure per Pupil (£)	41	54	*+32*	40	63	*+53*	+21
Computers per Pupil	0.10	0.16	*+60*	0.10	0.17	*+70*	+10
% Using ICT Regularly	71	90	*+27*	78	93	*+19*	-8
% Trained to Use ICT	84	94	*+12*	79	93	*+18*	+6
% Recently Updated Training	61	86	*+41*	55	85	*+54*	+13
% Schools Connected to Internet	89	100	*+12*	78	100	*+28*	+16

Notes: LEAs ranked by per pupil ICT funding; ranking fixed in 1998/1999. Outlier schools have been excluded (schools in the top or bottom 1% of either the computer per pupil or expenditure per pupil distributions). The number of schools in top LEAs is 191 and 229 in 1999/2000 and 2002/2003 respectively. The number of schools in bottom LEAs is 189 and 203 in 1999/2000 and 2002/2003 respectively.

Table 4 Expenditure and Use of ICT resources, before and after the policy, 'top LEAs' vs. 'bottom LEAs', *Secondary Schools*

	Secondary Schools						
	Top LEAs			Bottom LEAs			
	99/00	02/03	% Change	99/00	02/03	% Change	Bottom-Top, 99/00-02/03
ICT Expenditure per Pupil (£)	64	70	*+9*	59	66	*+12*	+3
Computers per Pupil	0.15	0.23	*+53*	0.16	0.23	*+44*	-9
% Using ICT Regularly	38	55	*+45*	38	57	*+50*	+5
% Trained to Use ICT	75	81	*+8*	75	88	*+17*	+9
% Recently Updated Training	50	68	*+36*	52	75	*+44*	+8
% Schools Connected to Internet	99	100	*+1*	98	100	*+2*	+1

Notes: LEAs ranked by per pupil ICT funding; ranking fixed in 1999/2000. Outlier schools have been excluded (schools in the top or bottom 1% of either the computer per pupil or expenditure per pupil distributions). The number of schools in top LEAs is 167 and 190 in 1999/2000 and 2002/2003 respectively. The number of schools in bottom LEAs is 183 and 188 in 1999/2000 and 2002/2003 respectively.

Table 5 Instrumental Variable Strategy; First Stage LEA Regressions

	ΔLog(ICT Funding per Pupil)	
	(1) OLS	(2) OLS
*Index*Policy-on*	0.894	0.913
	(0.078)**	(0.078)**
Index	-0.556	-0.593
	(0.080)**	(0.077)**
Sparsity		0.120
		(0.029)**
ΔLog(Pupil/Teachers)		0.030
		(0.566)
ΔLog(Number of Pupils)		-0.077
		(1.055)
ΔLog(Number of Schools)		0.413
		(0.363)
ΔLog(LEA School Expenditure/Pupils)		0.682
		(0.170)**
Constant	0.009	-0.121
	(0.028)	(0.032)**
Year Dummies	YES	YES
Observations	591	591
R-squared	0.62	0.64
F-Test on Excluded Instrument	*131.99*	*136.33*
R-squared on Excluded Instrument	*0.30*	*0.32*

Notes: Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Index is an LEA based indicator defined as fitted log share of ICT funding minus actual log share, in 1999/2000. Regressions are weighted by number of pupils in the LEA.

Table 6 Computers per Pupil; Power of the Instrument at school-level

	ΔLog(Computers per Pupil)			
	Primary Schools		Secondary Schools	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
*Index*Policy-on*	0.013	0.011	-0.004	-0.004
	(0.005)**	(0.004)**	(0.003)	(0.004)
Index	-0.003	-0.007	-0.010	-0.009
	(0.003)	(0.002)**	(0.003)**	(0.004)**
Sparsity		0.018		-0.007
		(0.005)**		(0.005)
ΔLog(Pupil/Teachers)		-0.007		-0.011
		(0.005)		(0.011)
ΔLog(Number of Pupils)		-0.056		-0.072
		(0.007)**		(0.018)**
ΔLog(% Special Needs Pupils)		0.002		-0.000
		(0.001)		(0.001)
ΔLog(% Free Meals Eligibility)		-0.000		0.002
		(0.002)		(0.003)
Constant	0.042	0.047	0.067	0.073
	(0.002)**	(0.002)**	(0.002)**	(0.002)**
Year Dummies	YES	YES	YES	YES
Observations	3613	3355	3920	3848
R-squared	0.28	0.32	0.32	0.33
F-Test on Excluded Instrument	*9.11*	*9.35*	*0.81*	*0.86*
R-squared on Excluded Instrument	*0.003*	*0.003*	*0.000*	*0.000*

Notes: Index is an LEA based indicator defined as fitted log share of ICT funding minus actual log share, in 1999/2000. Standard errors clustered at the LEA level in parentheses: * significant at 5%; ** significant at 1%. Outlier schools have been excluded (schools in the top or bottom 1% of either the computer per pupil or expenditure per pupil distribution). ICT variable comes from ICT School Survey. Other school-level variables come from the School Performance Tables and the Annual School Census.

Table 7 Change in proportion of students obtaining Level 4 or above in KS2 English and LEA per Pupil ICT Spending

	ΔLog(Proportion of Level 4 or above, KS2 English)		
	(1) OLS	(2) IV	(3) IV
ΔLog(ICT Funding per Pupil)	0.001	0.020	0.020
	(0.004)	(0.006)**	(0.006)**
Index	-0.002	-0.004	-0.001
	(0.002)	(0.003)	(0.002)
ΔLog(Pupil/Teachers)			0.023
			(0.055)
ΔLog(Number of Pupils)			0.142
			(0.119)
ΔLog(Number of Schools)			-0.035
			(0.036)
ΔLog(LEA School Expenditure/Pupils)			-0.029
			(0.015)
Sparsity			-0.022
			(0.004)**
Constant	0.065	0.066	0.075
	(0.002)**	(0.002)**	(0.004)**
Year Dummies	YES	YES	YES
Observations	591	591	591
R-squared	0.63	0.60	0.62

Notes: Index is an LEA based indicator defined as fitted log share of ICT funding minus actual log share, in 1999/2000. Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Regressions are weighted by number of pupils in the LEA.

Table 8 Change in proportion of students obtaining Level 4 or above in KS2 Mathematics and LEA per Pupil ICT Spending

	ΔLog(Proportion of Level 4 or above, KS2 Maths)		
	(1) OLS	(2) IV	(3) IV
ΔLog(ICT Funding per Pupil)	0.001	0.007	0.006
	(0.003)	(0.005)	(0.005)
Index	-0.002	-0.002	-0.000
	(0.002)	(0.002)	(0.002)
ΔLog(Pupil/Teachers)			-0.073
			(0.050)
ΔLog(Number of Pupils)			-0.016
			(0.113)
ΔLog(Number of Schools)			-0.077
			(0.038)*
ΔLog(LEA School Expenditure/Pupils)			-0.001
			(0.013)
Sparsity			-0.011
			(0.004)**
Constant	0.042	0.042	0.044
	(0.002)**	(0.002)**	(0.003)**
Year Dummies	YES	YES	YES
Observations	591	591	591
R-squared	0.57	0.57	0.58

Notes: Index is an LEA based indicator defined as fitted log share of ICT funding minus actual log share, in 1999/2000. Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Regressions are weighted by number of pupils in the LEA.

Table 9 Change in proportion of students obtaining Level 4 or above in KS2 Sciences and LEA per Pupil ICT Spending

	ΔLog(Proportion of Level 4 or above, KS2 Sciences)		
	(1) OLS	(2) IV	(3) IV
ΔLog(ICT Funding per Pupil)	0.002	0.016	0.014
	(0.003)	(0.008)*	(0.007)*
Index	-0.004	-0.006	-0.003
	(0.002)*	(0.002)*	(0.002)
ΔLog(Pupil/Teachers)			-0.067
			(0.047)
ΔLog(Number of Pupils)			-0.038
			(0.116)
ΔLog(Number of Schools)			0.030
			(0.041)
ΔLog(LEA School Expenditure/Pupils)			-0.011
			(0.016)
Sparsity			-0.018
			(0.004)**
Constant	0.082	0.082	0.088
	(0.003)**	(0.003)**	(0.004)**
Year Dummies	YES	YES	YES
Observations	591	591	591
R-squared	0.76	0.75	0.76

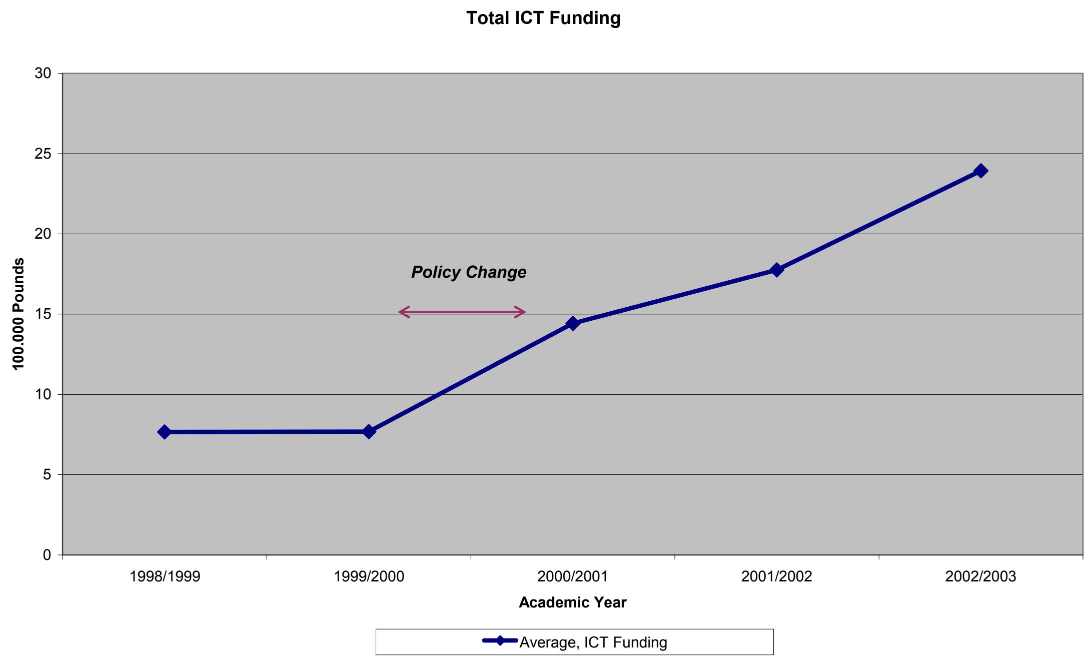
Notes: Index is an LEA based indicator defined as fitted log share of ICT funding minus actual log share, in 1999/2000. Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Regressions are weighted by number of pupils in the LEA.

Table 10 IV Estimates and Achievements: One Period Impact and Time-to-Build Policy Effects

	(1) English	(2) Maths	(3) Sciences
One Period Impact	0.013	0.005	0.006
(1999-2000 vs. 2000-2001)	(0.005)**	(0.004)	(0.004)
Time to Build Effect, 2 Periods after Policy Change	0.025	-0.005	0.017
(1999-2000 vs.2002-2003)	(0.012)*	(0.010)	(0.012)
Time to Build Effect, 3 Periods after Policy Change	0.030	0.019	0.029
(1999-2000 vs.2002-2003)	(0.011)**	(0.010)	(0.015)*
Year Dummies	YES	YES	YES
Other Controls	YES	YES	YES
Observations	295	295	295

Notes: Standard errors clustered at the LEA level in parentheses * significant at 5%; ** significant at 1%. Regressions are weighted by number of pupils in the LEA.

Figure 1 Trends in ICT funding; LEA level



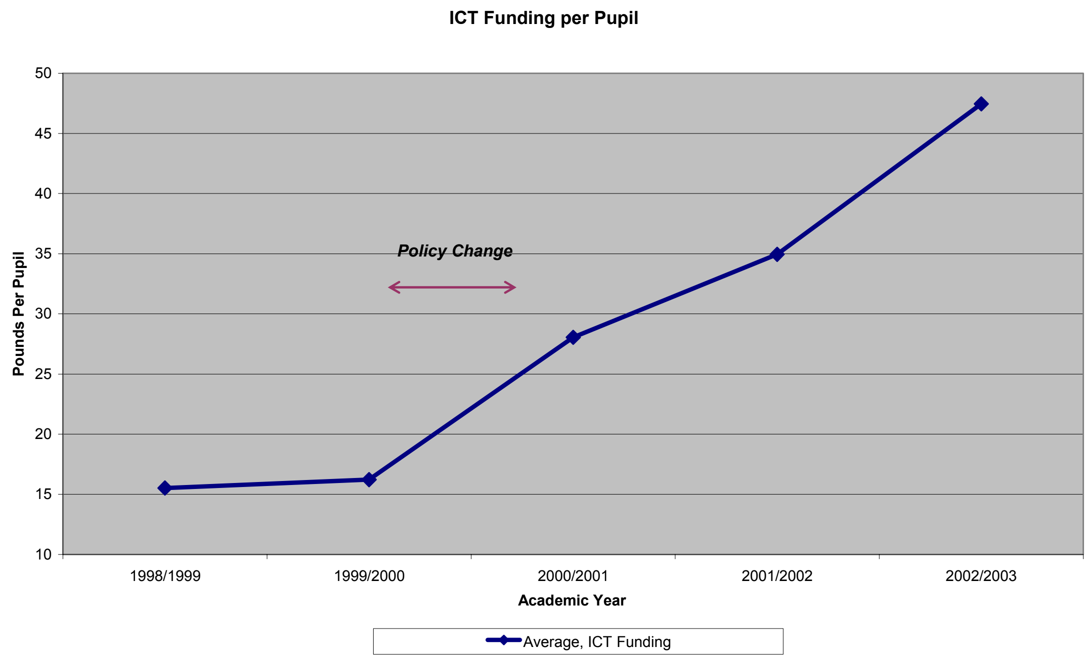
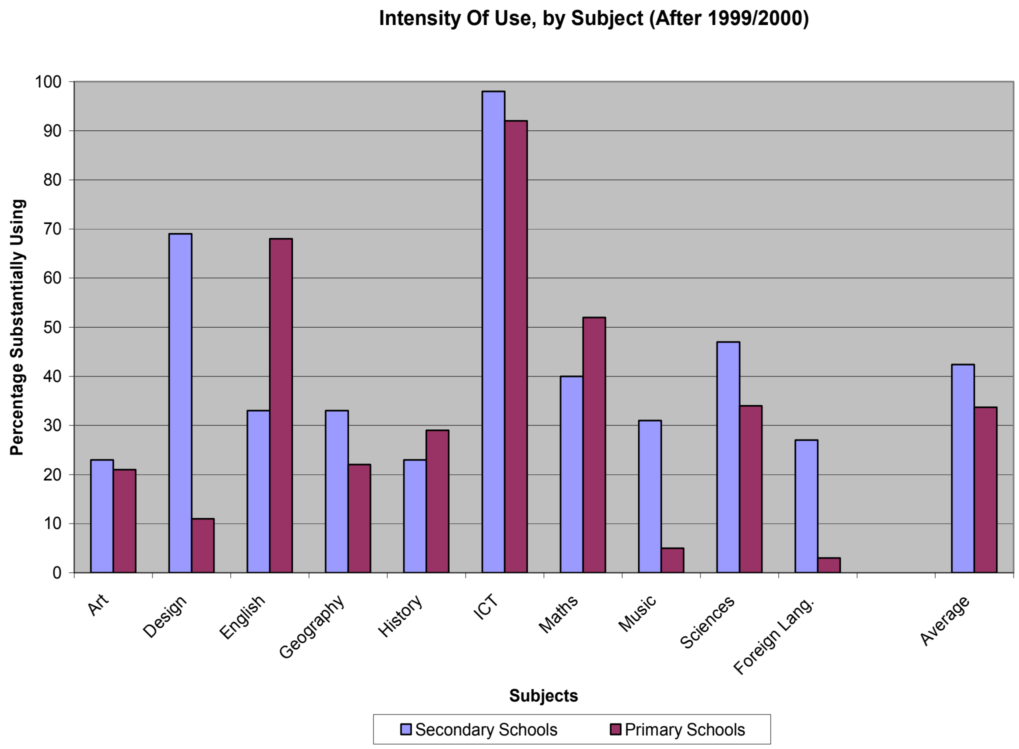
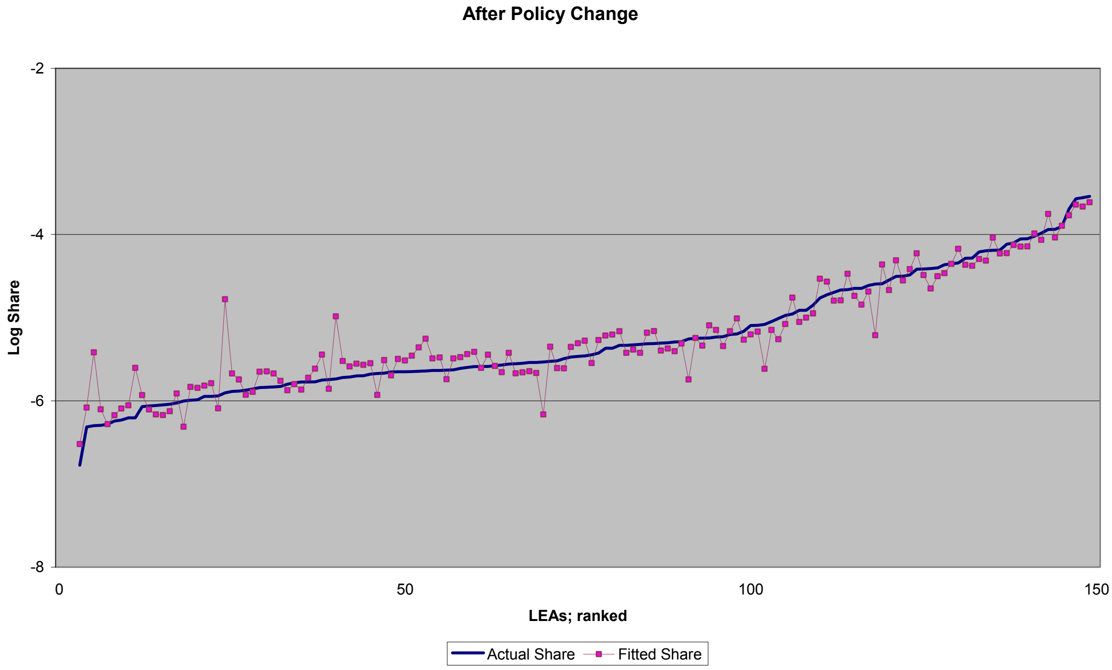


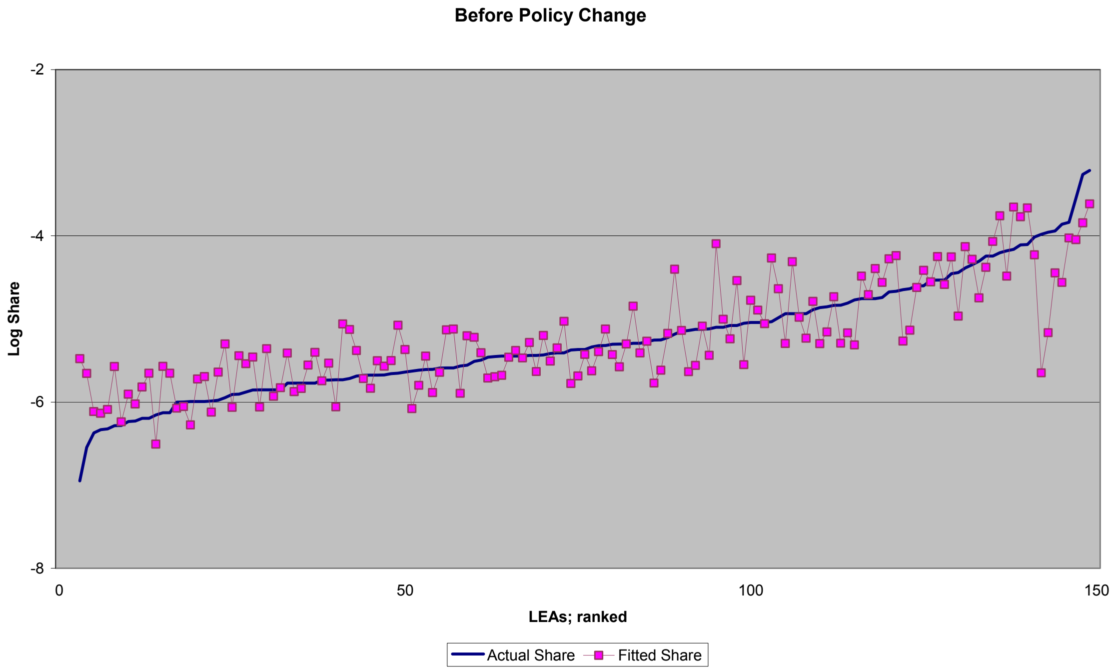
Figure 2 Use of ICT by Subject.



Notes: Data are averaged over the period 1999/2000-2002/2003. Intensity of use by main subject; statistics represent percentages of teachers substantially using computers and ICT support in their classes.

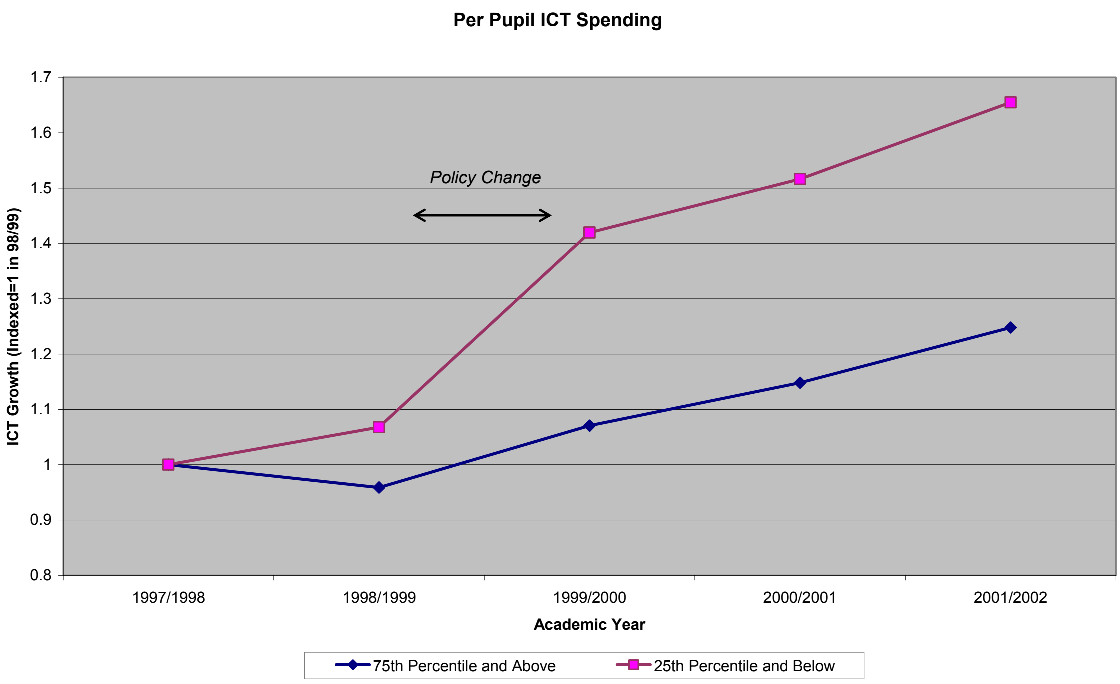
Figure 3 ICT funding Actual and Fitted, before and after the policy





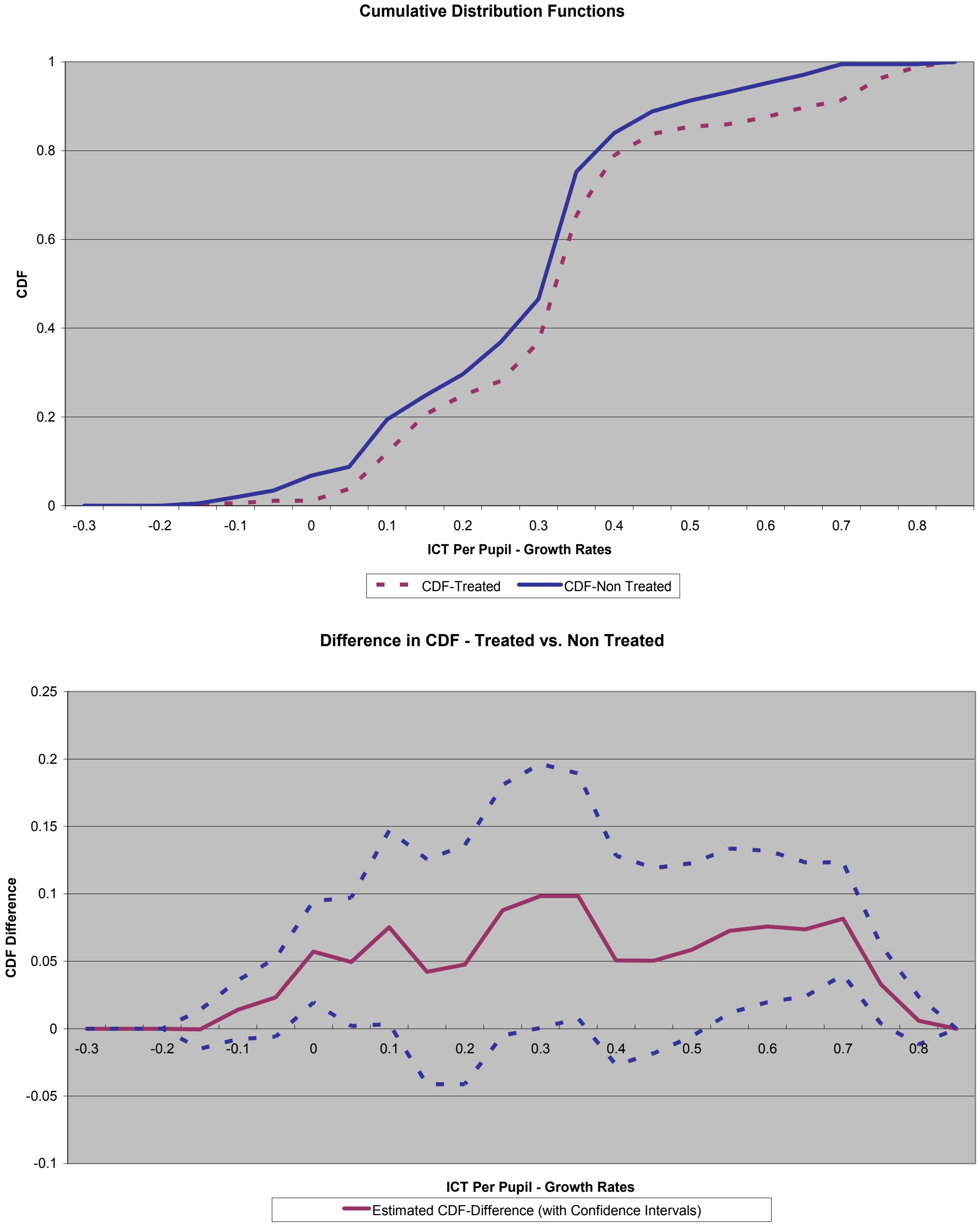
Notes: the three bottom LEAs have been dropped from the graphs; the excluded LEAs are “Corporation of London” (LEA 201), “Isle of Scilly” (LEA 420) and “Rutland” (LEA 857). These LEAs always rank at the very bottom (they have very few schools); all regressions results are robust to their exclusion.

Figure 4 ICT per pupil funding for 'top LEAs' (at or above the 75th percentile) and 'bottom LEAs' (at or below the 25th percentile) of the ICT distribution in 1999



Notes: LEAs ranked by ICT funding per pupil; ranking fixed in 1998/1999.

Figure 5 Impact of the Instrument and Average Causal Response (ACR) Interpretation



Notes: Instrument is binary version of Index; equals 1 for Winners (positive values of Index); equals 0 for Losers (negative values of Index). Growth rates expressed in percentage points/100 (1=100%). CDFs and Difference in CDFs computed over the common support of ICT funds per pupil, for treated and non-treated.

Appendix

Table A1 Is ICT Funding Crowding out other LEA funding?

	ΔLog(LEA Funding per Pupil) -net of ICT-		
ΔLog(ICT Funding per Pupil)	-0.034		-0.024
	(0.011)**		(0.010)**
*Index*Policy-on*		-0.069	-0.043
		(0.048)	(0.051)
Index		0.052	0.035
		(0.041)	(0.043)
ΔLog(Pupil/Teacher)	-0.281	-0.251	-0.297
	(0.154)	(0.157)	(0.156)
ΔLog(Number of Pupils)	2.848	2.635	2.762
	(0.554)**	(0.541)**	(0.547)**
ΔLog(Number of Schools)	-0.063	-0.024	-0.058
	(0.111)	(0.111)	(0.107)
Sparsity	-0.030	-0.036	-0.032
	(0.016)	(0.015)*	(0.016)*
Constant	0.090	0.082	0.087
	(0.005)**	(0.004)**	(0.004)**
Year Dummies	YES	YES	YES
Observations	591	596	591
R-squared	0.08	0.08	0.09

Notes: Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Index is an LEA based indicator defined as fitted log share of ICT funding minus actual log share, in 2000. Regressions are weighted by number of pupils in the LEA.

Table A2 Descriptive Statistics and Balancing Properties of the Instrument

Dependent Variable	(1) *Descriptive Statistics*	(2) *Correlation with Instrument*	(3) *Regression on Instrument*
% Achieving ≥ level 4, English;	0.033	-0.172	-0.017
growth rate 97-98	(0.040)		(0.010)
% Achieving ≥ level 4, Maths;	-0.057	0.026	0.003
growth rate 97-98	(0.050)		(0.011)
% Achieving ≥ level 4, Science;	0.006	-0.061	-0.006
growth rate 97-98	(0.039)		(0.008)
% Achieving ≥ level 4, English;	0.024	0.137	0.021
growth rate 97-98	(0.059)		(0.018)
Permanent Exclusion	0.300	-0.129	-0.048
Index, 1999	(0.154)		(0.034)
Total Number of	14534.42	-0.077	-1760.07
Crimes, 1999	(9384.33)		(2281.61)
Number of Teen	274.45	0.028	12.433
Pregnancies, 1999	(178.02)		(38.840)
Mean Household	21.515	0.062	0.573
Income, 1999 (thousand of £)	(3.794)		(0.604)
Total Number of Young	655.60	-0.069	-87.187
Unemployment Claimants, 1999	(521.74)		(122.40)

Notes: Column 1 presents averages of various dependent variables and standard deviations in parentheses. Column 2 reports pair-wise correlations between dependent variables and Index. Column 3 presents regression coefficients from separate regressions of the dependent variables on Index and a constant; standard errors in round brackets. Correlations and regression coefficients not significant at conventional levels.