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ABSTRACT

New Technology in Schools: Is There a Payoff?*

Despite its high relevance to current policy debates, estimating the causal effect of Information Communication Technology (ICT) investment on educational standards remains fraught with difficulties. In this paper, we exploit a change in the rules governing ICT funding across different school districts of England to devise an instrumental variable strategy to identify the causal impact of ICT expenditure on pupil outcomes. The approach identifies the effect of being a 'winner' or a 'loser' in the new system of ICT funding allocation to schools. Our findings suggest a positive impact on primary school performance in English and Science, though not for Mathematics. We reconcile our positive results with others in the literature by arguing that it is the joint effect of large increases in ICT funding coupled with a fertile background for making an efficient use of it that led to positive effects of ICT expenditure on educational performance in English primary schools.

JEL Classification: H52, I20, I28, J24

Keywords: Information and Communication Technology (ICT), pupil achievement

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1. Introduction

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

The UK government has motivated its sizable ICT investment in schools by stressing the importance of ICT in improving education levels. Recently the Secretary of State for Education has spoken of ICT as 'crucial to our drive to raise standards'.[1] It is envisaged that ICT should be widely used across the whole school curriculum, in all publicly funded schools (DfES, 2003; Ofsted, 2001). The positive rhetoric about ICT in the UK has been backed up by considerable government investment. Between 1998 and 2002, ICT expenditure in England almost doubled in secondary schools (from an average of about £40,100 to just under £75,300 per school, or around 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 educational 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 simple correlation between ICT and pupil performance, which casts serious doubt on the validity of findings. Starting with the study by Angrist and Lavy (2002), there has been a small number of economic studies that address this issue and apply more rigorous methods of analysis: none of them, with exception of

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

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.

In this paper, we look at the relationship between changes in ICT investment and changes in educational outcomes in England. To do so, we mainly rely on administrative data at the level of the Local Education Authority[2] 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 funding led to changes in ICT investment and subsequently changed educational outcomes. This 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 to interpret our findings.

Unlike previous studies in the economic literature, we find evidence for a positive causal impact of ICT investment on educational performance in primary schools. This is most evident in English test scores, where we also show evidence that there is high use of ICT for teaching purposes. Additionally, we find a positive, but less robust, effect on Science test scores, while we fail to detect any impact on achievement in Mathematics. We reconcile our positive results with others in the literature by arguing that it is the joint effect of large increases in ICT funding coupled with a fertile background for making an efficient use of it that led to positive effects of ICT expenditure on educational performance in English primary schools.

The rest of the paper is structured as follows. In Section 2, we present a brief review of the economic literature on computers and education. In Section 3, we discuss how ICT (mainly computers) is used in English schools and describe the changing policy context. In Section 4, we

[2] 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, intervening where a school is failing its pupils and for allocating funding to schools.

outline our identification strategy, 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 more controversial.[3]

Some empirical support for the effectiveness of CAI comes from the educational and psychology literature. Yet, the review provided in Kirkpatrick and Cuban (1998), suggests that the evidence for the effectiveness of ICT in schools is, at best, mixed. More importantly, the authors cast serious doubt on the methodological approach of existing studies. Evidence for the English experience in recent years is reported in Becta (2002) and Ofsted (2001), and similarly points to a positive link between high standards across the curriculum and ICT use in schools. However, as for most of the studies reviewed by Kirkpatrick and Cuban (1998), results are generally inferred from a simple 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 and that contemporaneously affect performance and technology. This gives rise to serious concern about the validity of the findings. In fact, this problem is well illustrated in the recent study by Fuchs and Woessman (2004), which uses international data from the Programme for International Student Assessment (PISA). The authors show that while the simple bivariate correlation between the availability of computers

[3] In fact, there are reasons to think computers in the classroom may in some situations be a distraction and displace other, more effective, teaching techniques.

at school and school performance is strongly and significantly positive, this becomes small and insignificant when other school characteristics are taken into account. This suggests that 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 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. 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. Their conclusions similarly suggest that the extra funds for computers and software did not have a positive impact on pupils' achievement. In the same spirit, Goolsbee and Guryan (2005) analyze the effect of a program in the US to subsidize schools' investment in Internet and communications. While they do not have a quasi-experimental setting, the authors try to isolate the program's effect from underlying trends, mainly by exploiting a regression discontinuity design. Although the program led to an increase in Internet connections, they find no impact on any measure of pupil achievement. Finally, Rouse *et al.* (2004) present results from a truly randomized study of a popular instructional computer program designed to improve language and reading skills in the US. Their estimates also suggest that the use of computer programs do not significantly help improve measures of language acquisition and reading skills.

An important exception to the body of work that reports no effects is Banerjee et al. (2004). Their analysis presents the results of a randomized policy evaluation administered in India, aimed at improving 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. Although these results can hardly be compared to findings from studies in developed countries (where the educational context is so different), the authors are the first to show (in a causal sense) that CAI may have the potential to improve the educational achievement of disadvantaged children.

In summary, the small number of studies addressing the ‘endogeneity’ issue report little evidence of a positive relationship between the use of computers and/or computer software and educational performance. This suggests 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. In the remainder of this paper, we consider these important, policy relevant issues in the context of the English school system.

3. ICT in English Schools

In 1997 the UK government announced plans to encourage the widespread application of ICT to teaching and learning in maintained schools.[4] The intention was to equip schools with modern ICT facilities, create a national framework with educational information and study material, and organize in-service training programs for teachers and school librarians (Ofsted, 2001). A target for the computer-pupil ratio was also set, with the aim of achieving a ratio 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). The increase in ICT 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 per pupil for LEAs.[5] The Figure displays a dramatic increase in resources from 2000 onwards (i.e. the Financial Year 1999/2000).[6]

[4] Maintained schools refer to all non-private sector schools in the UK; these are funded by Local Education Authorities, largely from central government grants.
[5] Figures are in real terms, deflated using the GDP deflator.
[6] 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).

Using information from the 'ICT Survey of Schools in England', we show how this translated into ICT use in schools in 2000 and 2003. 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, ICT expenditure per pupil is higher on average than the LEA figures would suggest. 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 change 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 over 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). Although secondary schools were better equipped with ICT in 2000, the greatest relative increase over time was

[7] For 2000 and 2002, we checked whether ICT expenditure per pupil coming from ICT-specific funding is consistent in the school surveys with the administrative data. We find that schools in the ICT survey report a lower allocation from this source. This may be due to the 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.

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. Hence, one might expect any effect of ‘computer-aided 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 16 and 3.5 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 increased the amount of ICT equipment.

Figure 2 provides additional information about the use of ICT in schools. It shows 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 from 2000 to 2003. 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). The non-ICT subject where ICT is most often used is design in secondary school, followed by 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, where ICT is ‘substantially used’ in about 56 percent of primary schools and 40 per of secondary schools. ICT is also relatively important in the teaching of Science.

The ICT Funding Mechanism

How is money allocated to schools to finance their use of ICT? Government grants for ICT funding are distributed to schools via their Local Education Authorities (LEAs). 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 put forward innovative and interesting proposals for the use of ICT funds; hence, funding depended on the importance attached to ICT by the LEA. 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 and an adjustment made for population density.

The change in the allocation mechanism created winners and losers among LEAs. 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, 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 the ICT funding allocation to LEAs was not made on the same basis before and after the policy change.[8] Hence some LEAs gained from the new system, but others lost - the magnitude of the gain or loss can be measured by the difference between the share of funding received by the LEA in the new system relative to the share it received in the old system.

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 graph shows that among the two groups, the relative 'winners' were LEAs at the lower part of the distribution in 1999, which

[8] 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.

benefited from massive increases in ICT funds after the policy change (they had an average growth rate of about 50 percent per year).

In Table 3, 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. Panel A 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) in 2000. However, as would be expected from the large relative increase in government funding to the latter group, the rate of increase in most school-level indicators is considerably higher in 'bottom LEAs' than in 'top LEAs'. In contrast, this pattern is far less clear for secondary schools (Panel B of Table 3), where the rate of increase in ICT expenditure per pupil is only slightly higher for schools in 'bottom LEAs' than '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 that ICT-specific funding from LEAs appears to be less important as a source of overall ICT expenditure.[9]

To conclude, the key features of the policy change that are important for the analysis are as follows: the basis for the funding allocation was very different in the old and new system; the change created 'winners' and 'losers'; the change had a larger impact on primary schools than on secondary schools.[10] In our analysis, we will 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

[9] 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).
[10] The change was not pre-empted by LEAs in how they were bidding for funding the year before the rule changed. This seems very unlikely; in fact, the funding share in the two pre-change years, 1999 and 2000, is very highly correlated.

LEA level. We argue that this provides an *exogenous* source of variation in ICT funding that can be used to analyze its impact on educational outcomes, overcoming potential endogeneity problems.

4. Analytical Framework and Identification

Because our identification strategy is based on a rule change at LEA level, we rely on data at this level of aggregation to devise an Instrumental Variable (IV) strategy. 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 the rule change created 'winners' and 'losers' among LEAs. The magnitude of gain or loss can be measured by 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] We argue that this provides us with an *exogenous* source of variation to predict the growth rate of ICT funding per pupil after the policy change. Hence our first-stage regression is:

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

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.

[11] There are various data constraints at school-level. For example, one needs to rely on retrospective information to construct changes in the computer/pupil ratio for schools. We do not have retrospective information on ICT expenditure per pupil. The school-level surveys are repeated cross sections, where very few schools are 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.

The second stage regression can be written as follows:

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

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 necessary as being a 'winner' or a 'loser' from the rule allocation change (reflected 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. However, in our analysis, 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, $Index_{it \geq 2001}$ = $Index_i$ * *Policy-on*) that is used for identification, and not $Index_i$ itself. This allows us to control for LEA fixed effects and hence remove this potential source of endogeneity from our instrument. Thus, we include in our regressions (both first and second stage) a full battery of LEA dummies. Our identification strategy is similar to the non-linear IV approach followed by Angrist and Lavy (2002).[13]

Notice that the validity of our identification strategy hinges on the possibility of controlling for LEA unobservable characteristics affecting ICT funding per pupil, as well as other educational inputs and outputs, by using LEA fixed effects over the period of analysis. Yet, our strategy would be flawed if $Index_i$ were picking up longer pre-policy trends, affecting how LEAs respond to the policy change and adjust to the new equilibrium, both in terms of inputs and output.

[13] 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 of an Instrumental Variable approach, which is valid when controlling for parametric functions of the rank itself.

Therefore, in Table 4, we relate $Index_i$ to pre-policy trends in LEA educational inputs and achievements, by looking at the average annualized growth rates of LEA funding per pupil (real terms) and average achievement in English, Mathematics and Science. Consistent series for LEA funding per pupil are available back to 1992/1993, whilst a consistent series on educational achievement can only be reconstructed back to 1995/1996 (importantly, we analyze the same variables used to evaluate the effect of ICT on educational achievement in primary schools). In Column 1, we present average annualized growth rates for 'winner' LEAs (LEAs that benefited from the policy change) and in Column 2 the same figures are given for 'loser' LEAs (those losing from the introduction of the new system). Column 3 presents the difference between these two groups. Finally, in Column 4, we regress average annualized growth rates for all LEAs on $Index_i$, to directly analyze the relationship between pre-policy trends and our instrument. As shown in Columns 3 and 4, we are not able to detect a significant relationship between our instrument and the pre-policy trends.[14]

Further, Figure 5 provides a graphical representation of the relationship between LEA funding per pupil and being a 'winner' or a 'loser' on account of the policy change. The graph shows that total expenditure per pupil (in real terms) fell almost constantly between 1992/1993 and 1999/2000, before the policy change.[15] Yet, the trend for winners and losers shows a very similar pattern. It moves in parallel for 'winners' and 'losers' throughout this period. Importantly for our analysis, the trend is identical in the few years prior to the policy change. This is highly reassuring for the validity of our IV strategy.

[14] Notice that we also tested whether $Index_i$ is related to a number of observable LEA characteristics before the period under analysis, including the number of crimes and teenage pregnancies, mean household income and young unemployment claims, all in 1999. We find no significant relationship between these variables and our instrument. This provides additional evidence as to the validity of our strategy.

[15] Notice that, in nominal terms, expenditure per pupil has been constantly growing over the period under analysis. The total nominal growth rate for England was about 6%, between 1992/1993 and 1999/2000, and 27% between 1999/2000 and 2002/2003.

One might ask whether instrumenting for the change in ICT funding is really necessary when estimating regressions at LEA level. For example, it could be argued that there is exogenous variation in the growth of ICT funding as this is largely determined by central government; or that, 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.[16] Secondly, because LEAs must provide matched funding to 'ICT-specific' grants, the level of LEA funding (and relevant school expenditure) will reflect the extent to which LEAs prioritize ICT investments; growing ICT expenditure may come at the cost of a reduction in other forms of investments, i.e. crowding out non-ICT specific LEA expenditure. 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. Yet, provided our instrument is orthogonal to the dynamics of other (non-ICT) LEA expenditure, the IV approach will still isolate the effect of additional ICT investment in schools on pupils' achievement. In Table A1 of the Appendix, we 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 analysis is 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

[16] Ashenfelter and Krueger (1994) show this to be a problem that is exacerbated in a longitudinal context.

Imbens (1995) as 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, the 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.

5. Results

First Stage Regressions

Regressions are based on administrative data at LEA level for the years 1999-2003. All variables are specified as changes in logs, 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). First stage regressions are shown in Table 5. In Column 1, we show the relationship between the instrument and the change in ICT funding per pupil, controlling for LEA unobservable trends by using a full set of LEA dummies, as well as a set of year dummies. 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.[17] Finally, in Column 3, we include $Index_i$ (rather than LEA dummies) to control for LEA specific trends and to save degrees of freedom (this of course makes very little difference at all since it is only because time-varying controls are included that the coefficient on *Index*Policy-on* is not identical in Columns 2 and 3).

The key parameter of interest is the estimated coefficient on *Index*Policy-on*, which is positive and highly significant in all 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

[17] In fact, when using a full battery of LEA dummies, the sparsity factor (which is constant over time) drops-out.

of the variation observed in the growth rate of ICT after the policy change. 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.[18]

In Table 6, we report similar specifications at 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 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, though it is much less powerful than in regressions specified at the LEA level.[19] 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 0.11 percentage points.[20] In contrast, the estimated coefficient is zero for secondary schools. Given the discussion in Section 3, it is perhaps 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.

The Effect of ICT Funding on Educational Outcomes

In England, compulsory education is organized into 4 Key Stages (KS1 to 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,

[18] Remember that our instrument is the difference between the actual logarithmic share of ICT funding accruing to an LEA in 2000, and the log share of funds computed applying the formula for 2000 (see Figure 3, bottom panel). It therefore measures the change in the relative position in the distribution of ICT funds across LEAs.

[19] 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.

[20] The estimated coefficient at the school level is 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 partly rely on ICT-specific 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.

14 and 16 respectively. The test at age 11 is taken at the end of primary school (KS2). 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 is set out in the National Curriculum. Government targets for pupils of age 11 are based around the percentage of pupils that attain ‘level 4’ or above. Hence, this is the measure of performance recorded in the School Performance Tables and used in our analysis (at LEA level).

In the three Panels of Table 7, we report results from LEA-level regressions, where the outcome variables measure examination performance at KS2 (age 11) in English (Panel A), Mathematics (Panel B) and Science (Panel C). [21] All Panels include three specifications. In Column 1, we show basic OLS results. In Columns 2 and 3 we show results from IV regressions, including LEA dummies (Column 2), and then adding all other controls (Column 3).

Starting from the top Panel, the OLS regression shows no relationship between ICT funding per pupil and performance in English. In contrast, all 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 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.[22] In Panel B, similar regressions are shown,

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

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

where performance in Mathematics is the dependent variable. In this case, the relationship between ICT funding per pupil and the measure of performance is always positive, but insignificant, with the estimated coefficients being very close to zero. Finally, in Panel C, results show no relationship between ICT funding and performance in Science for the OLS regressions. However, the coefficient is positive and borderline significant in the IV regressions (10 percent level in Columns 2 and 3). In this case, a doubling of ICT funding per pupil leads to an increase of 1.6 percentage points in the proportion of pupils achieving level 4 or above.

Robustness

Some issues remain to be discussed. First, as shown in the earlier Figures, our IV strategy is more binding for the years immediately before and after the rule change for the allocation of ICT funds. An important issue is how the results are affected if we apply the IV strategy to the model in Equation (1) over the years 1999-2000 and 2000-2001 only. Second, 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. For example, it may be that 'winner' LEAs gradually redistributed resources down to a growing number of schools. 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 8. 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 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.[23] Results for English are reported in the first Column and show a positive and significant effect of ICT, even when attention is confined to the immediate aftermath of the policy change: the estimated impact is 0.013, and is significant at the 1 percent level. Also, comparison of 1999-2000 with subsequent periods (2001-2002 and 2002-

[23] In this specification we use $Index_i$ to control for LEA specific trends, rather than a full set of LEA dummies. This is because we are using fewer observations than in our main analysis. In fact, when using LEA dummies, we find very similar point estimates, but with reduced statistical significance.

2003) suggests the policy change took some time to produce its full effect. For Science, the estimated impact over 1999-2000 and 2000-2001 is significantly reduced and the IV estimates in Table 7 mainly capture an effect of the policy emerging in the period 2002-2003, which is estimated to be as large as for English. We find no significant positive impact of ICT on Maths scores.

Finally, since our regressions are based on a five year LEA panel, we also address the possibility of serial correlation which may spuriously increase the precision of our estimates. To do so, we follow the methodology of Bertrand et al. (2004) and collapse the data to just two observations per LEA – one before and one after the policy change. When we do this, we still find a positive and significant impact of ICT investment on English achievement (coefficient 0.023, significant at the 5 percent level) and a marginally significant effect on Science grades (0.019, significant at the 10 percent level); and no impact for Mathematics.

Interpretation of the Findings

The evidence discussed so far suggests that, in the English context, where a policy change in 2001 induced *large* relative changes in ICT funding, ICT expenditure has led to significant improvements in school performance in English and Science tests at age 11, though not for Mathematics. 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). It 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' (LEAs in the top quartile of our $Index_i$ distribution) the average annual growth rate of ICT funds was about 50 percent after the policy change (i.e. over 2001-2003) as compared to a much smaller change of 20 percent for big 'losers' (LEAs in the bottom quartile of the $Index_i$ distribution).

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, we implement the method of 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. 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 function (CDF) 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.[24] Results are depicted in the top panel of Figure 5. 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 6, 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

[24] 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.

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.

Furthermore, it seems that LEAs benefiting most from the policy change were LEAs with lower overall expenditure per pupil, but better educational standards (as measured by exam pass rates and truancy rates), suggesting that resources were redirected to areas that were in a better position to use them efficiently.[25] Additionally, evidence discussed in Section 3 suggests that new technology was already in place in English schools since the mid-Nineties, and that money redirected after the policy change was mainly spent in updating resources and teachers' skills.

To summarize, in the English case, it appears to be the joint effect of large increases in ICT funding and a fertile background for making an efficient use of it, that led to positive effects of ICT expenditure on educational performance. This helps to reconcile our results with the most recent evidence in Goolsbee and Guryan (2005). In their case, funding was diverted to the most disadvantaged areas and, as they admit, there are doubts about whether resources were actually used, not least because teachers were "novice or completely inexperienced with computers" (page 24). Additionally, while their analysis deals with the impact of internet access in schools, we study the impact of overall ICT expenditure. We have provided evidence that almost all our schools were fully equipped with internet access for the period under analysis. This suggests that investment may have been concentrated in more effective areas, such as teacher training and support.

Finally, we provide one further remark about the interpretation of our estimates. Evidence in Table A1 suggests that our estimates are virtually free from crowding out effects that ICT expenditure may have on other type of educational expenditure. In fact, the relationship between (the instrumented growth rate of) ICT expenditure and other LEA funds is both statistically

[25] See our web-appendix posted at: http://personal.lse.ac.uk/silvao/ICTWebAppendix_LEARanked.xls

insignificant, and small (bearing in mind that full crowding out would correspond to a coefficient of -1). This suggests that our findings should be interpreted as pertaining to the effect of extra resources invested in ICT, holding constant other inputs.

6. Conclusion

It is difficult to firmly establish a causal relationship between computers and educational outcomes and there are only a small number of studies in the economic literature which try to do so. 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 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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Figure 1:
Trends in ICT funding per Pupil; LEA level.

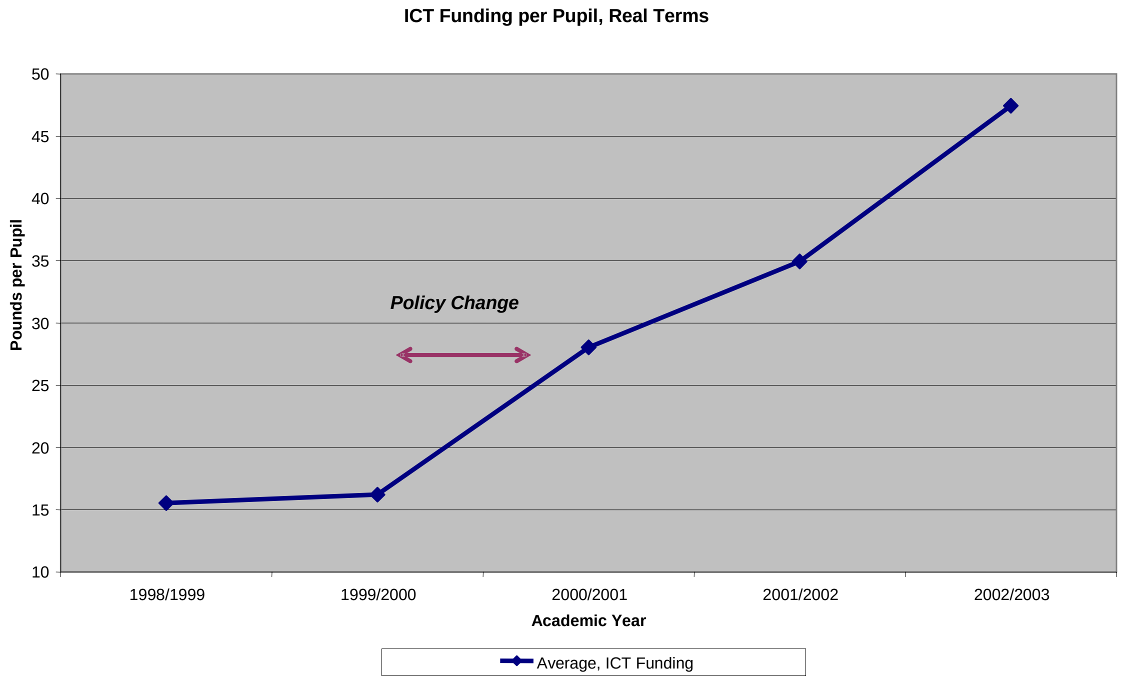


Table 1:
Trends in ICT Expenditure and Use of ICT resources;
***Primary* and *Secondary* Schools.**

	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

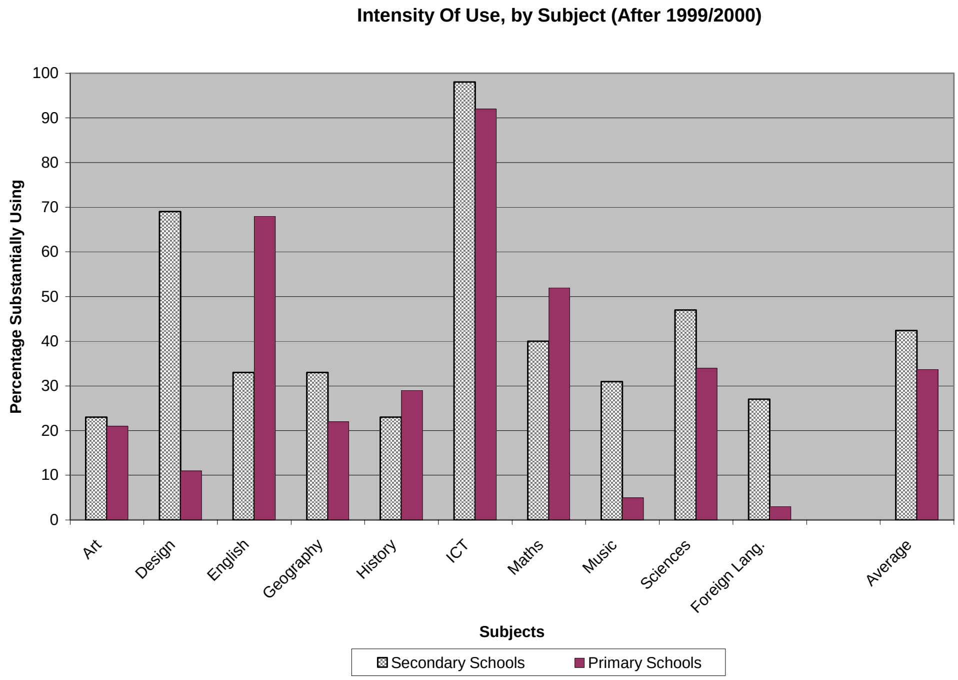
Notes: Outlier schools have been excluded (schools in the top or bottom 1% of the distribution of either computers per pupil or expenditure per pupil). Number of primary schools: 627 in 1999/2000; 810 in 2002/2003. Number of secondary schools: 616 in 1999/2000; 714 in 2002/2003.

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

	1999/2000	2001/2002	% Change
Panel A: Primary Schools			
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*
Total Expenditure	£10,000	£14,100	*+41*
Panel B: Secondary Schools			
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*
Total Expenditure	£56,500	£76,000	*+34.5*

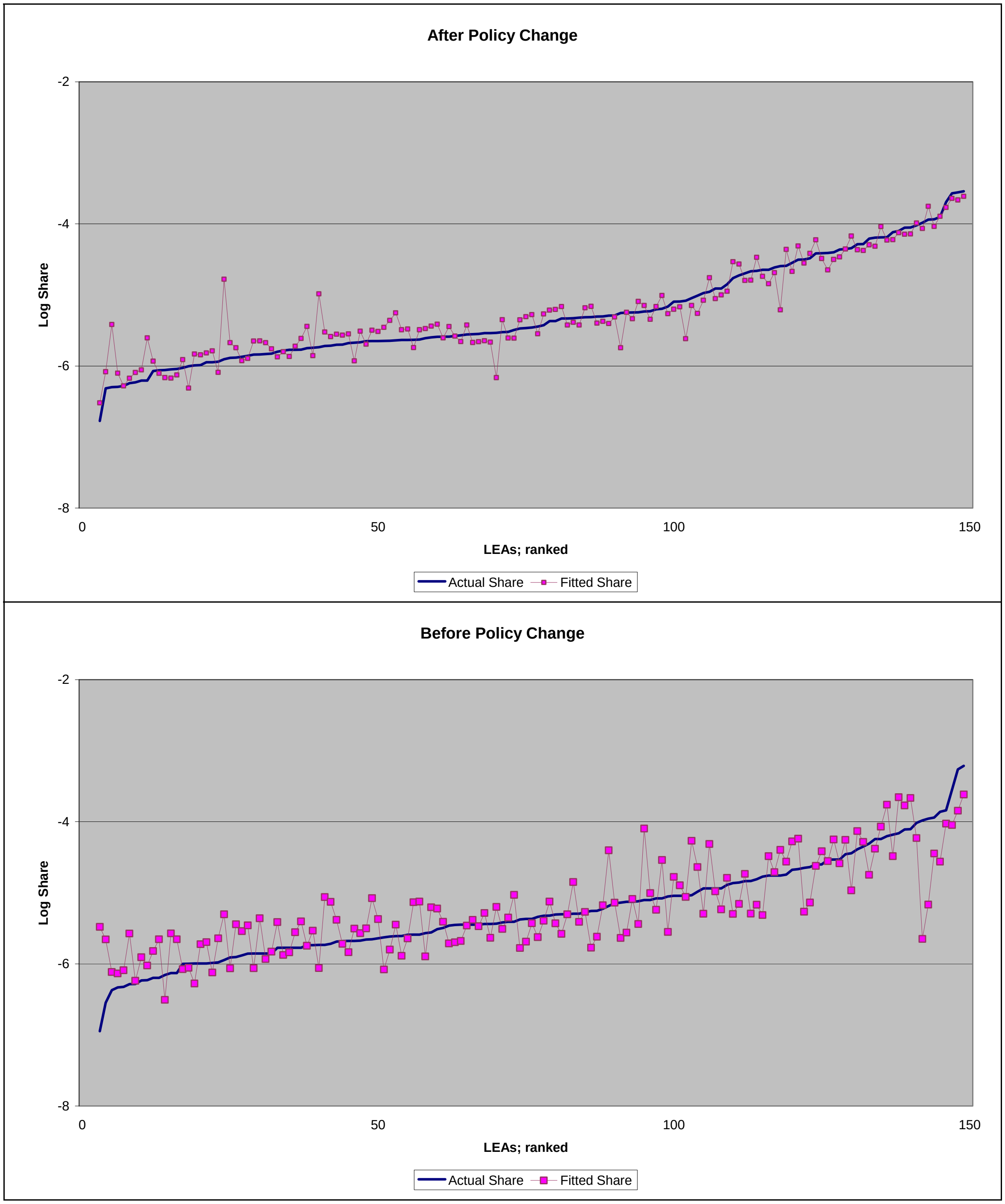
Notes: Table reports percentages of total ICT expenditure devoted to different items and average total ICT expenditure in primary schools and secondary schools, in years 2000 and 2002. Outlier schools have been excluded (schools in the top or bottom 1% of the distribution of either computers per pupil 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.

Figure 2:
Use of ICT by Subject.



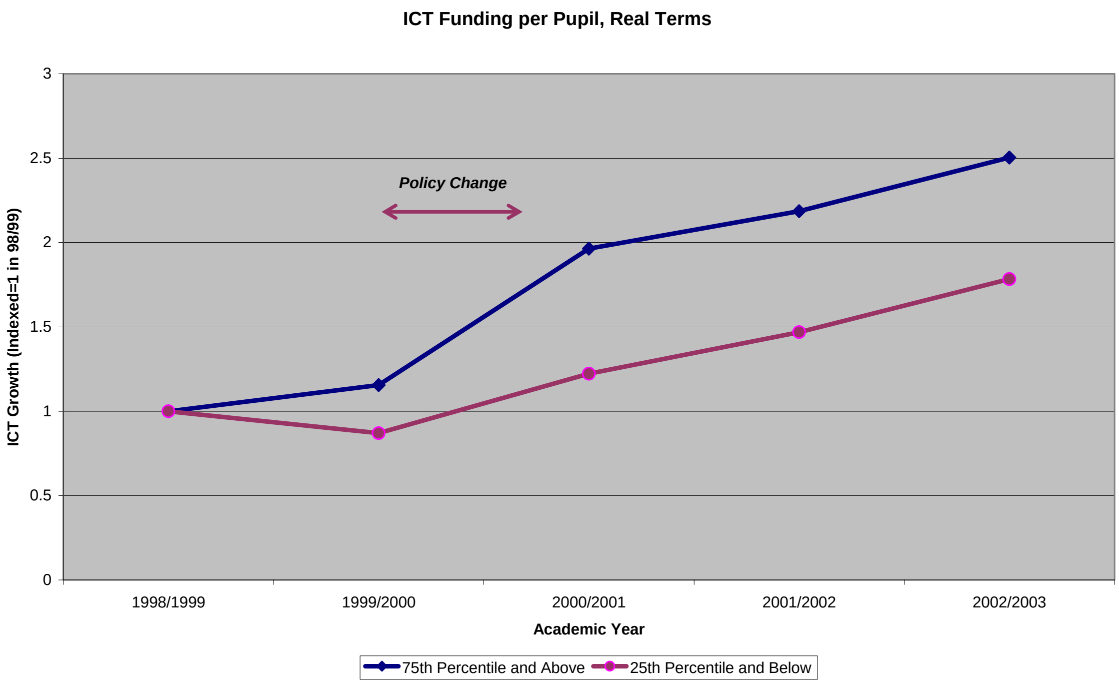
Notes: Data are averaged over the period 1999/2000-2002/2003. Intensity of use by main subject; statistics represent the percentage of teachers substantially using computers and ICT support in their classes.

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 regression 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. 'Top LEAs' include LEAs at or above the 75th percentile of the ICT funding per pupil distribution in 1998/1999; 'Bottom LEAs' include LEAs at or below the 25th percentile of the ICT funding per pupil distribution in 1998/1999. ICT funding per pupil in 'Top' LEAs was £23.5 in 1998/1999; ICT funding per pupil in 'Bottom' LEAs was £10 in 1998/1999.

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

	Bottom LEAs			Top LEAs			
	99/00	02/03	% Change	99/00	02/03	% Change	Bottom-Top, 99/00-02/03
Panel A: Primary Schools							
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
Panel B: Secondary Schools							
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

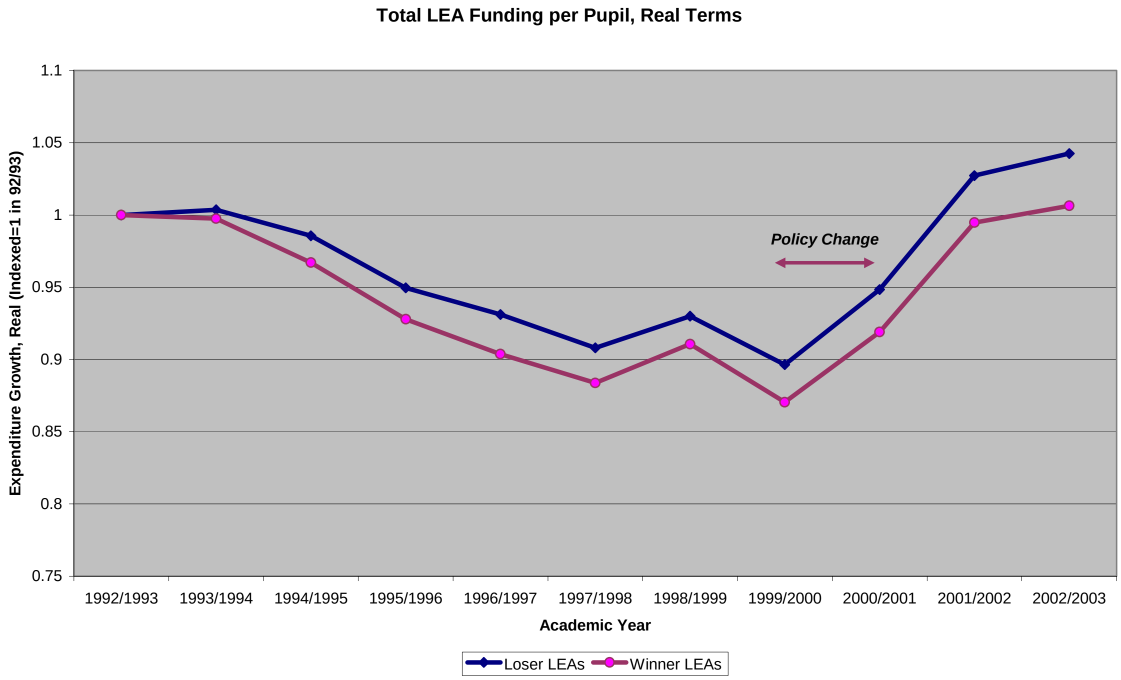
Notes: LEAs ranked by ICT funding per pupil; ranking fixed in 1998/1999. 'Top LEAs' include LEAs at or above the 75th percentile of the ICT funding per pupil distribution in 1998/1999; 'Bottom LEAs' include LEAs at or below the 25th percentile of the ICT funding per pupil distribution in 1998/1999. Outlier 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 primary schools in top LEAs is 191 and 229 in 1999/2000 and 2002/2003 respectively; the number of primary schools in bottom LEAs is 189 and 203 in 1999/2000 and 2002/2003 respectively. The number of secondary schools in top LEAs is 167 and 190 in 1999/2000 and 2002/2003 respectively; the number of secondary schools in bottom LEAs is 183 and 188 in 1999/2000 and 2002/2003 respectively.

Table 4:
Pre-Policy Trends and Balancing Properties of the Instrument.

Average Annualized Growth Rate Over Period.	(1) *'Winner' LEAs*	(2) *'Loser' LEAs*	(3) *Difference 'Winners'-'Losers'*	(4) *Regression, Dep. Variable on Index*
LEA Funding/Pupil, Real Terms	-0.019	-0.016	-0.003	-0.002
(1992/1993 to 1999/2000)	(0.002)	(0.002)	(0.003)	(0.003)
KS2 Achievements, English	0.068	0.073	-0.005	-0.007
(1995/1996 to 1999/2000)	(0.002)	(0.003)	(0.003)	(0.004)
KS2 Achievements, Maths	0.071	0.075	-0.004	-0.006
(1995/1996 to 1999/2000)	(0.002)	(0.003)	(0.003)	(0.004)
KS2 Achievements, Sciences	0.079	0.083	-0.004	-0.005
(1995/1996 to 1999/2000)	(0.002)	(0.003)	(0.004)	(0.005)

Notes: 'Winner' LEAs are LEAs with non-negative values of Index, i.e. those gaining from the introduction of the formula based policy; 'Loser' LEAs are LEAs with negative values of Index, i.e. those losing from the introduction of the formula based policy. 79 LEAs out of 149 are in the 'Winner' category (53%). Columns 1 and 2 presents average growth rates of the variables of interest (listed in Column 1), and standard errors in parentheses, for 'winner' and 'loser' LEAs, respectively. Column 3 reports differences in average annualized growth rates for the variables of interest, and standard errors in parentheses, between 'Winner' and 'Loser' LEAs. Column 4 reports the coefficient from separate regressions of average annualized growth rates of the variables of interest on Index (and a constant). Mean differences and regression coefficients not significant at conventional levels.

Figure 5:
Trends in Total LEA Funding Per Pupil for 'Winner' and 'Loser' LEAs.



Notes: 'Winner' LEAs are LEAs with non-negative values of Index, i.e. those gaining from the introduction of the formula based policy; 'loser' LEAs are LEAs with negative values of Index, i.e. those losing from the introduction of the formula based policy. Average LEA expenditure per pupil in 'Winner' LEAs was £3540 in 1992/1993; Average LEA expenditure per pupil in 'Loser' LEAs was £3600 in 1992/1993.

Table 5:
Instrumental Variable Strategy; First Stage, LEA Level Regressions.

	ΔLog(ICT Funding per Pupil)		
	(1) OLS	(2) OLS	(3) OLS
*Index*Policy-on*	0.894	0.902	0.901
	(0.090)**	(0.090)**	(0.080)**
Index	--	--	-0.582
			(0.078)**
R-squared	0.64	0.64	0.62
Year Dummies	YES	YES	YES
Controls	NO	YES	YES
LEA Dummies	YES	YES	NO
Observations	591	591	591
F-Test on Excluded Instrument	*99.00*	*100.40*	*133.63*
R-squared on Excluded Instrument	*0.32*	*0.32*	*0.31*

Notes: Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Index is an LEA based indicator defined as the fitted log share of ICT funding minus actual log share, in 1999/2000. Regressions are weighted by the number of pupils in the LEA. Controls include a sparsity factor and the log-change of number of pupils, number of schools and pupil/teacher ratio; all varying at the LEA level.

Table 6:
Computers per Pupil; Power of the Instrument at School-Level.

	ΔLog(Computers per Pupil)	
	Primary Schools	Secondary Schools
	(1) OLS	(2) OLS
*Index*Policy-on*	0.011	-0.004
	(0.004)**	(0.004)
R-Squared	0.37	0.37
Year Dummies	YES	YES
Controls	YES	YES
LEA Dummies	YES	YES
Observations	3355	3848
F-Test on Excluded Instrument	*9.85*	*0.92*
R-squared on Excluded Instrument	*0.003*	*0.000*

Notes: Index is an LEA based indicator defined as the 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). The ICT variable comes from ICT School Survey. Other school-level variables come from the School Performance Tables and the Annual School Census. Controls include the log-change of the number of pupils, pupil/teacher ratio, fraction of pupils with special educational needs, fraction of pupils eligible for free school meals (varying at the school level), and a sparsity factor (varying at the LEA level).

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

	(1) OLS	(2) IV	(3) IV
Panel A: ΔLog(Proportion of Level 4 or above, KS2 English)			
ΔLog(ICT Funding per Pupil)	0.004	0.020	0.022
	(0.004)	(0.007)**	(0.008)**
R-Squared	0.69	0.67	0.67
Panel B: ΔLog(Proportion of Level 4 or above, KS2 Mathematics)			
ΔLog(ICT Funding per Pupil)	-0.006	0.007	0.002
	(0.004)	(0.006)	(0.006)
R-Squared	0.40	0.39	0.49
Panel C: ΔLog(Proportion of Level 4 or above, KS2 Science)			
ΔLog(ICT Funding per Pupil)	0.004	0.016	0.016
	(0.003)	(0.009)	(0.009)
R-Squared	0.79	0.78	0.79
Year Dummies	YES	YES	YES
Controls	NO	NO	YES
LEA Dummies	YES	YES	YES
Observations	591	591	591

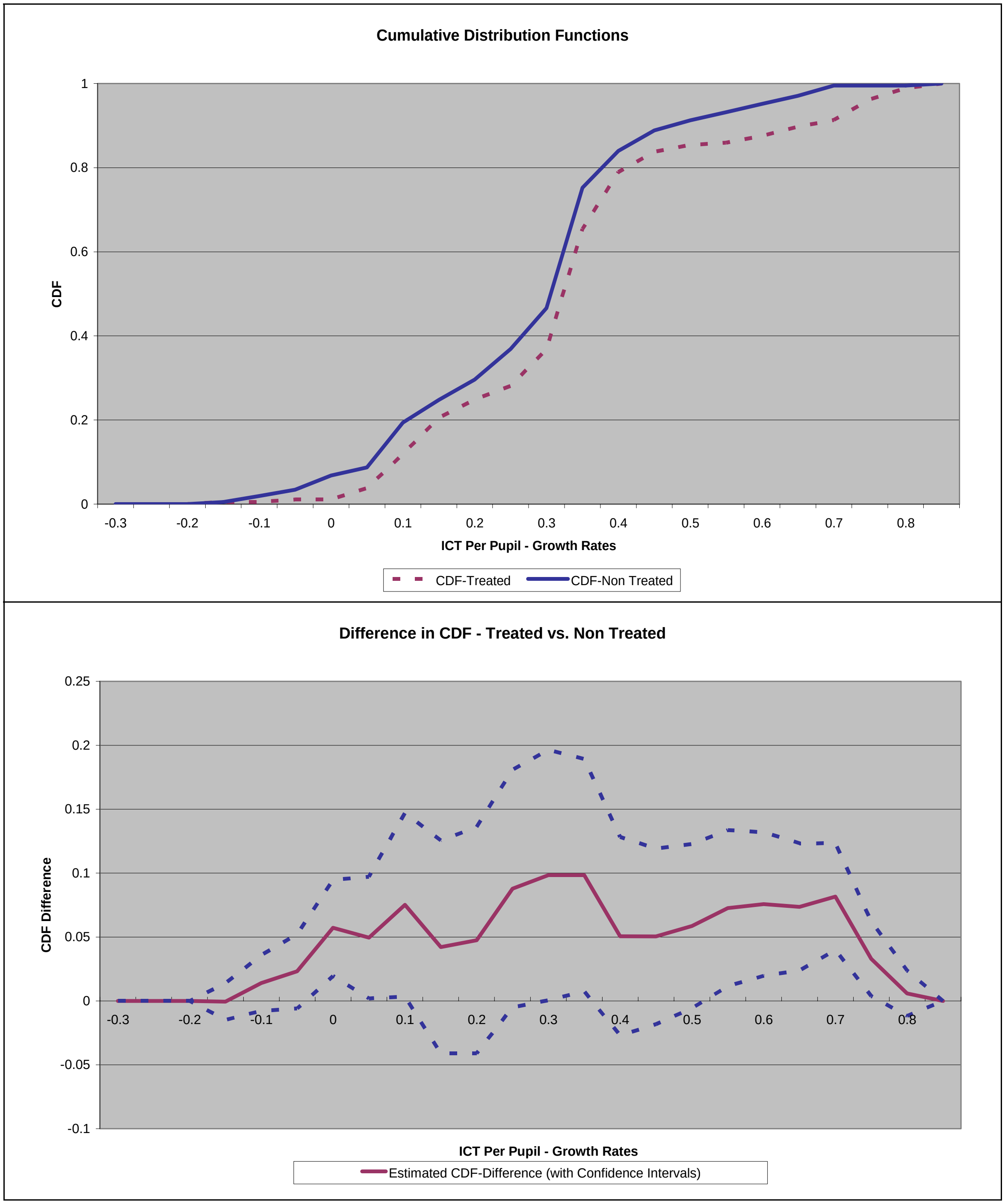
Notes: Index is an LEA based indicator defined as the fitted log share of ICT funding minus actual log share, in 1999/2000. Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Regressions are weighted by the number of pupils in the LEA. Controls include a sparsity factor and the log-change of the number of pupils, number of schools and pupil/teacher ratio; all varying at the LEA level.

Table 8:
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	0.026	-0.005	0.017
after Policy Change			
(1999-2000 vs.2002-2003)	(0.013)*	(0.010)	(0.012)
Time to Build Effect, 3 Periods	0.031	0.019	0.030
after Policy Change			
(1999-2000 vs.2002-2003)	(0.011)**	(0.011)	(0.015)*
Year Dummies	YES	YES	YES
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 the number of pupils in the LEA. Controls include a sparsity factor and the log-change of the number of pupils, number of schools and pupil/teacher ratio; all varying at the LEA level. Regressions also include *Index* to control for LEA specific trends.

Figure 6:
Impact of the Instrument and Average Causal Response (ACR) Interpretation.



Notes: Instrument is a binary version of Index: 1 for Winners (non-negative values of Index); 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-		
	(1) OLS	2 (OLS)	3 (IV)
ΔLog(ICT Funding per Pupil)	-0.039 (0.013)**		-0.061 (0.052)
*Index*Policy-on*	--	-0.064 (0.057)	--
R-squared	0.23	0.22	0.22
Year Dummies	YES	YES	YES
Controls	YES	YES	YES
LEA Dummies	YES	YES	YES
Observations	591	591	591
F-Test on Excluded Instrument	--	--	*72.93*
R-squared on Excluded Instrument	--	--	*0.24*

Notes: Standard errors clustered at the LEA level in parentheses; * significant at 5%; ** significant at 1%. Index is an LEA based indicator defined as the fitted log share of ICT funding minus actual log share, in 2000. Regressions are weighted by number of pupils in the LEA. Controls include a sparsity factor and the log-change of the number of pupils, number of schools and pupil/teacher ratio; all varying at the LEA level. In Column 3, *ΔLog(ICT Funding per Pupil)* is instrumented using *Index*Policy-on*.