A Short-Run View of What Computers Do: Evidence from a UK Tax Incentive

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Abstract: We study the short-run, causal effect of Information and Communication Technology (ICT) adoption on the employment and wage distribution, providing direct insight into how ICT alters the demand for work within the firm. We exploit a unique natural experiment generated by a generous tax allowance on ICT investments for small UK firms and find that the primary short-run effect of ICT is to complement non-routine cognitive-intensive work. At the same time, we find less extensive substitution for routine cognitive work, a result at odds with existing long-run estimates. We find no effect of ICT on manual work in the short run. Overall, ICT raises average labor productivity within the firm.

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1. Introduction

Policymakers and researchers have recently been interested in the relationship between firms' adoption of new information and communication technologies (ICT) and the changing demand for different types of work. A prominent example is the work by Autor, Levy and Murnane (2003), who address the question of "what computers do" by presenting evidence suggesting that ICT complements work that involves the execution of complex, non-routine workplace tasks, while to an equal or greater extent substituting for work that is highly routine. Substantial long-run evidence consistent with the Autor et al. (2003) thesis has since been presented,[2] yet an important question remains: what is the direct, short-run impact of ICT investment on the demand for different types of labor within the firm?

A key challenge in testing the Autor et al. (2003) hypothesis is that over long time horizons the relative supply of different labor types is endogenous to the extent of ICT adoption. For instance, Acemoglu (1998, 2002, 2007) argues that the choice of new technologies in which to invest is in part determined by the relative supply of skilled labor, and that ultimately the two interact over time—i.e., in the long run, the incentive to invest in skill also responds to innovation. This two-way interaction is also emphasized by Goldin and Katz (2008) who document the long-run "race" between education and technology.[3] As a result, in order to isolate the direct relationship between ICT adoption and the demand for different types of labor, it is important to hold both the supply of skill and the level of technology fixed.

[2]For instance, Autor et al. (2003) present correlations between the use of personal computers (PCs) and the prevalence of non-routine work over the period 1960 to 1998, while Akcomak, Kok and Rojas-Romagosa (2013) do so over the period 1997 to 2006. Michaels, Natraj and van Reenen (2014) take an international perspective and report conditional correlations between ICT and labor market outcomes for 11 countries over 25 years. Doms and Lewis (2006), Beaudry, Doms and Lewis (2010), as well as Autor and Dorn (2013) pursue a more causal interpretation by documenting a positive, long-run relationship between the (likely exogenous) historical concentration of routine tasks across local labor markets and subsequent workplace computer adoption. Autor and Dorn (2013) find that these historically routine intensive regions also show rising wages and employment at the tail ends of the skill distribution relative to middle skilled jobs ("job polarization"). Autor, Dorn and Hanson (2013a,b) also pursue this "tasks-based" approach to the labor market and adopt a similar indirect supply-side identification strategy. Acemoglu and Autor (2011) as well as Draca, Sadun and van Reenen (2006) provide recent reviews of this literature.

[3]Another potentially important long-run general equilibrium effect is suggested by Autor and Dorn (2013). They argue that the observed increase in the demand for low-skill, non-routine-intensive service work (e.g., health care, massage therapy, food service, etc.) throughout the 1990s and 2000s could be a consequence of ICT adoption. Specifically, they argue that the increased demand for these services may come from workers who are complementary to ICT and have therefore seen their incomes, and marginal propensity to consume services, rise.

In this paper we exploit an unanticipated ICT tax incentive in order to identify the direct impact of ICT investment on firms' demand for different types of workers.[4] Specifically, we exploit a generous one-time, narrowly-targeted 100 percent tax credit for investments in ICT that was made available to small UK firms between 2000 and 2004.[5] We first show that the introduction of this targeted tax credit differentially altered ICT investment between similar small and large firms. Here we rely on the identifying assumption that the two groups of firms had similar investment patterns prior to the introduction of the policy and, in addition, that there were no external shocks during the investment period that would differentially affect investment incentives across the two groups. We conduct a host of robustness checks to offer evidence in favor of these assumptions.

Given that both the supply of skill and the level of technology are likely fixed over the short horizon studied here, we exploit this variation to isolate the direct labor demand response to these investments, producing estimates that are independent of long-run, general equilibrium effects. To do this we adopt the job-type classification from Acemoglu and Autor (2011), finding that workers engaged in non-routine, cognitive-intensive production tasks saw immediate gains from the ICT investment, though the average worker also experienced an increase in earnings and employment. On the other hand, routine, cognitive workers were displaced and also suffered a loss in earnings, yet these effects were small relative to the gains to non-routine, cognitive workers. Overall, the pattern is consistent with an outward shift in the demand for non-routine, cognitive-intensive production tasks in response to the investment in ICT and a simultaneous, but much smaller, inward shift in the demand for routine, cognitive work.

We also find that the economic magnitudes are important: the ICT tax incentive led to a 4 to 10 percent increase in ICT investment each year that it was available, equivalent to an additional

[4] Our analysis complements a handful of existing studies on the short-run consequences of ICT adoption. These are based on less comprehensive datasets and have a sightly different focus. For instance, Bartel, Ichniowski and Shaw (2007) use survey responses from 212 US valve-making plants in 2002 to study potential plant-level mechanisms through which computers may enhance productivity. Among other results, they find that the "adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of machine operators, notably technical and problem-solving skills, and with the adoption of new human resource practices to support these skills." In a related paper, Brynjolfsson and Hitt (2003) study 527 large US firms over 1987-1994 and provide evidence for overall short-run firm-level productivity gains in response to computer investments, though they do not study the effect of computers on labor demand. Doms, Dunne and Troske (1997) focus on the manufacturing sector and present industry-level correlations that suggest that computers increase demand for non-production labor.

[5] See http://www.hmrc.gov.uk/manuals/camanual/CA23130.htm for official documentation.

1000 U.K. pounds of ICT investment per year for the upper bound estimate. This led firms to increase their employment of non-routine, cognitive workers by about 3 percent, while reducing employment of routine, cognitive workers by about 1 percent, with an associated wage increase for the former of about 13 pounds per week and moderate decline for the latter. At the same time, there was no statistically significant effect on manual (non-cognitive) workers. These findings are also consistent with industry estimates we present, which find the largest effects within the financial sector and the wholesale and retail trade sector, parts of the economy that are intensive in cognitive work and may have been likely to adopt ICT during the period we examine.[6] We note that the existing literature has typically exploited industry-level variation, such that our firm-level research design allows us to paint a more complete, and precise, portrait of the industry-specific effects.

Since exogenous variation in ICT investment is difficult to find, causal evidence on the direct consequences of investing in these technologies is rare.[7] An exception, and the analysis most closely related to ours, is provided by Akerman, Gaarder and Mogstad (2013), who study the effect of the sequential rollout of broadband internet across Norway on firm productivity and the wage distribution within firms. Our paper complements their work in that we also exploit a natural experiment in order to generate firm- and worker-level estimates. However, instead of focusing narrowly on the impact of internet access, we estimate the firm level effects of adopting computer hardware, software and other ICT capital. This also distinguishes our work from a recent literature that proxies ICT adoption with either the number of workers that uses a PC or the number of PCs in the workplace (see for example Beaudry et al., 2010, Autor and Dorn, 2013, and much of the literature surveyed in Acemoglu and Autor, 2011). Importantly, since PC purchases and broadband internet access are only one aspect of the larger ICT revolution, complementarity or substitution across ICT capital types will lead to biased estimates of their effects when they are

[6] One hypothesis is that to the extent that ICT innovation is moving up the "skill ladder", the impact of ICT on low-skill work in the manufacturing sector in the 1980s and 1990s may have given way to more extensive replacement of middle-skill back-office work in the 2000s.

[7] While many of the existing contributions only present conditional correlations, attempts to identify the causal effects of ICT on workers go back at least to Krueger (1993) and DiNardo and Pischke (1997).

estimated individually.[8] In this sense our estimates can be seen as reflecting the unbiased effect of ICT, inclusive of cross-capital interactions.

Finally, we note that temporary tax incentives, like the one explored here, are a popular vehicle to promote investment. However, there is little convincing evidence on the efficacy of such policies. Our paper therefore contributes to a long debate that goes back at least to Hall and Jorgenson (1967), and is most closely related to two recent contributions that exploit similar tax incentive programs, Cohen and Cummins (2006) and House and Shapiro (2008).[9]

The remainder of this article is organized as follows: we begin with a simple model that highlights the effect of ICT investments on the relative demand for labor types within the firm. We next describe the details of the tax policy and our data sources in Section 3. Section 4.1 presents estimates of the tax incentive's impact on firm investment decisions and Section 4.2 presents estimates of the impact of ICT on labor market outcomes. We offer some concluding remarks in Section 5.

2. Theory

In this section we consider a generalized model of firm production.[10] In doing so, we characterize the relationship between investments in ICT capital and the relative demand for two types of labor, which we refer to as routine and non-routine.[11] In keeping with our short-run approach, we assume that labor is supplied inelastically and the firm's technology is fixed. We show that the labor demand response to ICT investment hinges on four elasticities: the own price elasticity

[8] For example, the productivity of a PC is likely enhanced in combination with broadband internet access and an email system. However, note that the various ICT capital types may be complements or substitutes in their effect on worker outcomes. This is highlighted by Garicano and Rossi-Hansberg (2006) who argue that the adoption of communication technologies (such as mobile phones) will increase the return to problem solving (non-routine cognitive work), while reducing the knowledge-content of production (routine) work. In contrast, the labor market effects of adopting information-acquisition technologies (such as broadband internet) are likely to increase the knowledge-content and, therefore, the return to production (routine) work. Of course, ICT technologies may possess both of these features to some extent, so it is not clear how to isolate the relevant parameters.

[9] For other representative contributions to this debate see Auerbach and Hassett (1991, 1992), Cummins, Hassett and Hubbard (1994, 1996), Goolsbee (1998), or Chirinko, Fazzari and Meyer (1999).

[10] The setup and logic presented here follows Lafortune, Tessada and González-Velosa (2013) and Lewis (2013).

[11] In the empirics we explore the consequences for "routine cognitive", "non-routine cognitive", "routine manual" and "non-routine manual" labor types. For clarity, we abstract from the cognitive-manual distinction in the model presented here.

of demand for ICT capital, the output elasticity of ICT investment, and the relative elasticities of substitution between ICT and each labor type.

Consider a firm with a homogenous, continuous and twice-differentiable production function $Y = F(K, N, R)$, where K reflects the use of ICT capital, N is the use of non-routine labor and R is the use of routine labor within the firm. The first order condition representing the firm's demand for ICT capital is given by $\tilde{r} = F_K$, where $\tilde{r}$ is the *effective* price of a unit of ICT capital and the right hand side indicates the partial derivative of the production function with respect to ICT capital. We assume that the effective price of ICT is a function of the nominal price as well as the discounted value of any future tax savings the firm receives from a one unit increase in its stock of ICT—formally, $\tilde{r} = g(r, v^{\text{tax}})$, where $g_r > 0$ and $g_v < 0$.

Totally differentiating the first order condition for ICT capital we get $KF_{KK} d\ln K + NF_{KN} d\ln N + RF_{KR} d\ln R = 0$. Given the homogeneity of the production function we also know that $KF_{KK} + NF_{KN} + RF_{KR} = 0$, which can be combined with the previous total differential to get the following condition for the growth in the firm's demand for ICT capital:

$$d\ln K = \frac{NF_{KN}}{NF_{KN} + RF_{KR}} d\ln N + \frac{RF_{KR}}{NF_{KN} + RF_{KR}} d\ln R \tag{1}$$

Totally differentiating the production function we also have that

$$d\ln Y = \frac{\tilde{r}K}{Y} d\ln K + \frac{w^N N}{Y} d\ln N + \frac{w^R R}{Y} d\ln R \tag{2}$$

where w^N is the wage paid to non-routine labor, w^R is the wage paid to routine labor, and the fractions reflect the income shares of each input which we denote as θ_K, θ_N and θ_R, respectively. Subtracting $d\ln K$ from both sides of (2) and substituting (1) into (2), we can rearrange terms to get the following condition:

$$\underbrace{d\ln N - d\ln R}_{\Delta\text{Relative Labor Demand}} = \underbrace{\left(\frac{NF_{KN} + RF_{KR}}{Y\theta_N\theta_R}\right)}_{\text{Positive Constant}} \underbrace{\left(\frac{F_{KN}}{F_N} - \frac{F_{KR}}{F_R}\right)^{-1}}_{\text{ICT-Labor Elasticity}} \underbrace{\left(d\ln(\tilde{r}K) - d\ln y\right)}_{\text{ICT Investment}-\text{Output Growth}} \tag{3}$$

The first term on the right hand side is positive since $NF_{KN} + RF_{KR} = -KF_{KK} > 0$. The second term is positive when ICT is "q-complementary" to non-routine labor and negative when q-complementary to routine labor. This follows from the fact that the term is equivalent to the formal definition of q-complementarity, which can be alternatively stated as $\partial \ln \left(\frac{w^N}{w^R} \right) / \partial \ln K > 0$ for the case in which ICT is complementary to non-routine labor.[12]

Finally, the last term reflects the growth in capital's income share, which we decompose to highlight the fact that we are ultimately interested in a rise in ICT investment due to an exogenous reduction in the effective price of capital. In the empirics, this reduction is due to a U.K. tax incentive, which in the model can be seen as a rise in v^{tax} and which therefore reduces the effective price of a unit of ICT capital, $\tilde{r}$. This then results in an overall rise in ICT investment when the own price elasticity of ICT capital is greater than one, so that ICT investment is positive. When this is true, growth in the ICT investment-output gap (the capital share) is positive as long as the elasticity of output with respect to ICT investment is less than one.

Equation (3) suggests two testable hypotheses. First, when $\partial \ln \left(\frac{w^N}{w^R} \right) / \partial \ln K > 0$ so that a rise in the ICT capital stock raises the relative return to non-routine labor, then this constitutes evidence of complementarity between non-routine labor and ICT. Second, conditional on non-routine labor-ICT complementarity, a rise in ICT investment will (assuming the ICT-output elasticity is less than one) induce a rise in the relative demand for non-routine labor—i.e., $d \ln N - d \ln R > 0$. A rise in ICT capital investment therefore serves as a relative labor demand shock that may raise the relative wage and employment of non-routine workers.

3. Policy Experiment & Data Sources

Our research design explores the fundamental relationship between ICT and labor demand described in the model above by exploiting a unique natural experiment generated by a generous 100 percent first year tax allowance (FYA) on ICT investments available to small firms in the

[12]The literature often assumes a nested-CES production function of the form $Y = \left[(U^\alpha + K^\alpha)^{\rho/\alpha} + S^\rho \right]^{1/\rho}$, where U, K and S are unskilled labor, capital and skilled labor, respectively. In this case, $\partial \ln \left(\frac{w^S}{w^U} \right) / \partial \ln K > 0$ as long as $\alpha > \rho$—i.e., as long as capital and unskilled labor are more substitutable than skilled labor is with the nest of those factors.

UK. This policy represented a particularly large investment incentive, as it allowed businesses to write off the entire cost of ICT investments against their taxable profits. The following types of investments were eligible for the tax allowance:[5]

- Computer equipment comprising computers (ranging from small palmtop organizers to large systems), computer peripherals such as keyboards, printers etc; cabling and other equipment to link computers to each other, or to data networks such as the internet; and dedicated electrical systems for computers.
- High-tech communications technologies comprising WAP (wireless application protocol) phones, 3rd generation (3G) mobile phones and equipment with similar applications and functionality; and set-top boxes that are connected to televisions and are capable of receiving and transmitting information from and to data networks such as the internet.
- Software for use with computers or high-tech communications technologies. This covers all computer software, including new software for use on computers bought before April 1, 2000 and the costs of creating web sites.

To identify the impact of the policy, we exploit both the timing of its introduction as well as its targeted nature. The tax incentive was introduced on April 1, 2000, was initially scheduled to expire on March 31, 2003, but was then extended until March 31, 2004. The tax incentive was further restricted to ”small businesses” which her Majesty’s Revenue and Customs (HMRC) defined as ones that satisfy at least two of the following criteria: annual turnover of no more than £2.8 million, total assets of no more than £1.4 million, and no more than 50 employees.[13] We note that employment is overwhelmingly the key criterion—i.e., there are very few firms with fewer than 51 employees but more than £2.8 million in turnover or £1.4 million in assets.

3.1. Data Sources

Although our primary objective is to estimate the impact of the tax incentive on worker outcomes, as a first step we provide firm-level evidence on the magnitude of investments made by firms in

[13]For the remainder of this article we use the term ”small firm” as a synonym for the official HMRC definition.

response to the incentive. To do this, we exploit two data sources collected by the UK Office of National Statistics. First, we use data from the UK Quarterly Capital Expenditure Survey (QCES) which collects capital expenditure data by asset type for a random sample of 26,000 to 32,000 firms quarterly. Specifically, we exploit data on investments in computer hardware, software and ”other ICT”. Unfortunately, these variables are only collected for our treatment period, 2000 to 2004, and so we supplement them with data drawn from the Annual Census of Production Respondent’s Database (ARD), which contains data on plant and machinery investments (inclusive of ICT purchases) over the period 1997-2007. This allows us to provide evidence on pre-period trends in investment—a key to our identification strategy. The ARD is drawn from an underlying register of the universe of UK businesses and is the UK equivalent of the US Longitudinal Respondents Database. The data consist of a large, representative random sample of businesses with fewer than 100 or 250 employees, depending on the year (and the universe of firms above these thresholds, though we set aside these firms in our empirics).[14] We focus on firms within the range 40 to 60 employees, and using the combined ARD and QCES datasets for 2000 to 2004 we calculate that computer hardware, software and other ICT investment was 21 percent of total plant and machinery investment for this group of firms.[15]

To implement our research design with respect to workers we exploit another unique dataset, the UK Annual Survey of Household Earnings (ASHE), a representative one percent sample of workers drawn from an employer survey. The dataset provides detailed information about the earnings and hours worked of UK workers along with basic employment variables such as the detailed industry and occupation of the worker.[16] Importantly—and unusually—the survey also includes the number of employees associated with each worker’s firm, information that we exploit in order to link each worker’s employer to the eligibility criteria of the tax incentive. We include only those workers who work for private companies, since these workers are effectively ”treated” by the tax incentive. It is also worth noting that because the ASHE earnings data is provided by

[14] Each of the datasets is a repeated cross-section with a large panel dimension, a feature that will be important when comparing growth rates of various firm-level variables, as discussed below. For a comprehensive description of the ARD see Criscuolo and Martin (2009) or for a summary see Breinlich and Criscuolo (2011).

[15] We are more specific about our sample selection in Section 4.

[16] Earnings values are deflated using the UK CPI.

employers, rather than employees, it is much more accurate in this dimension relative to other surveys.

4. Research Design & Empirical Analysis

Our primary objective is to explore the within-firm impact of the policy-induced ICT investments on workers, and we undertake this analysis in Section 4.2. However, as a first step we estimate the investment response by firms to the incentive in order to determine whether the magnitude was indeed substantial and therefore likely to have impacted workers to an important extent.

4.1. Firm Response to the Tax Incentive

We start by establishing a relationship between firm eligibility for the tax incentive and investments in ICT among eligible firms. Since HMRC's definition of a small business was not introduced for this particular policy, we argue that eligibility for businesses close to the size threshold was effectively randomly assigned.[17] We therefore consider small businesses—as defined by HMRC—to be exogenously treated with the tax incentive, while all remaining businesses serve as the control group.

4.1.1. Features of the Firm Sample

Since firm size is correlated with a variety of other firm characteristics that may also be correlated with our dependent variables, we restrict our analysis to firms within a fairly narrow window around HMRC's size cutoff. To be more precise, an unbiased estimate of the tax incentive's impact requires that there are no group-specific trends that are correlated both with a firm's *a priori* eligibility for the tax incentive and the firm's pattern of ICT investment. As a first step, we restrict our sample to firms with 40 to 60 employees, values chosen simply as the nearest round numbers for which average pre-treatment growth rates for key firm variables were insignificantly

[17] One might think that firms may endogenously sort to ”just below” or ”just above” this size cutoff if many other policies or aspects of business in the UK are implicitly linked to this HMRC definition. However, we show below that this concern is not likely to be important in our context.

Table 1: Treatment vs. Control Group 1997-1999 (pre-treatment)

	Treatment Group (40-50)			Control Group (51-60)			Difference		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Diff.	t-Stat.	Norm. Diff.
A. Firms (ARD)									
Turnover ('000 $)	2888	1821.33	1116.86	4714	8663.55	19779.31	-6842.22	-23.69	-0.345
Employment	2888	45.08	4.90	4757	51.77	6.22	-6.69	-52.16	-0.845
Labor Productivity	2876	20.22	13.73	4653	32.56	29.76	-12.34	-24.40	-0.377
Investment ('000 $)									
Net Total Investment	2880	89.79	269.18	4695	191.57	631.42	-101.78	-9.70	-0.148
Plant & Machinery	2887	48.78	125.79	4746	110.76	343.76	-61.97	-11.24	-0.169
B. Workers (ASHE)									
Weekly Earnings ($)	7374	818.10	719.80	4278	805.82	664.73	12.28	0.93	0.013
Weekly Hours	7379	37.87	12.64	4279	36.98	12.70	0.89	3.66	0.050
Age	7379	39.38	12.64	4279	39.70	12.49	-0.32	-1.31	-0.018
% Male	7379	66.28	47.28	4279	63.66	48.10	2.62	2.86	0.039
C. 2-Digit SIC Industry by Employment Panel									
Firms (ARD)									
Δ Turnover	645	0.01	1.29	555	-0.03	1.30	0.04	0.55	0.022
Δ Labor Productivity	631	0.00	1.01	542	-0.06	1.00	0.06	0.96	0.040
Δ P & M Invesmtent	604	-0.04	1.68	525	-0.08	1.88	0.04	0.41	0.017
Workers (ASHE)									
Δ Earnings	729	0.07	0.81	550	0.05	0.92	0.03	0.55	0.022
Δ Hours Worked	731	0.04	0.70	551	0.01	0.80	0.04	0.86	0.034

Notes: Panel A reports sample summary statistics from the ARD firm sample, while panel B displays sample summary statistics for the ASHE worker sample. Panel C reports year-to-year growth rates for a panel comprised of 2-digit SIC-industry-by-employment cells. The reported growth rates are based on sampling-weighted cell means. The reported t-statistics are for a test of the pre-treatment difference in means between the treatment and control groups. In addition to the traditional t-statistic, $T = (\bar{X}_1 - \bar{X}_2)/\sqrt{S_1^2/N_1 + S_2^2/N_2}$, we follow Imbens and Wooldridge (2009) and also report the normalized difference, $ND = (\bar{X}_1 - \bar{X}_2)/\sqrt{S_1^2 + S_2^2}$, where $\bar{X}_i$, S_i^2, and N_i denote the sample mean, variance, and size of group i, respectively. As a rule of thumb, Imbens and Wooldridge (2009) suggest that a normalized difference of less than 1/4 indicates reasonable treatment and control groups within research designs of the type we pursue here.

different across the two groups.[18]

Table 1 reports a comparison of several pre-treatment-period firm (ARD sample, panel A) as well as worker (ASHE sample, panel B) characteristics for the sample of firms within the 40 to 60 employee range and on either side of the eligibility threshold. Finally, we exploit the panel dimension of the data and calculate average annual growth rates within 2-digit SIC industry by employment cells (panel C). First, we note that it is unsurprising that the *levels* of several variables

[18]When adopting the next largest window, 35 to 65 employees, the growth rate of labor productivity is significantly different across the two groups. Note that in restricting our sample we clearly trade off external validity for internal validity and our results should therefore be interpreted in this light.

are significantly different from one another across the firm-size threshold, which simply emphasizes the strong correlation between firm size and various other firm features. Our research design relies instead on common growth *trends*. Indeed, the comparisons of growth rates in panel C of Table 1 indicate that firms both above and below the size cutoff were moving along comparable trajectories prior to the introduction of the tax incentive. In particular, the finding of no significant difference in trends in the pre-period for the dependent variables we will focus on, labor productivity and investments in plant and machinery, is comforting.[19]

As a stronger test of the common trends assumption, we also regress a firm size indicator ($SMALL_i$) on the pooled pre-treatment average annual growth rates listed in Table 1, separately for firms and workers.[20] With respect to firms, we estimate the following specification across all industry-employment cells (denoted i) in our sample for the period 1997 through 1999:

$$SMALL_i = \underset{(0.015)}{0.536} - \underset{(0.0099)}{0.0002}\widehat{\Delta Inv}_i - \underset{(0.0175)}{0.0035}\widehat{\Delta Turn}_i + \underset{(0.0218)}{0.0144}\widehat{\Delta LabProd}_i \quad (\text{N=1108, R}^2\text{=0.0005})$$

where $\widehat{\Delta X}_i$ represents the average annual growth rate in outcome X associated with firm i and the standard errors for each of the estimated coefficients is in parentheses below the estimate. None of the regressors predicts firm size in the pre-treatment period, in support of the common trends assumption. With respect to workers (k), we analogously estimate the following regression:

$$SMALL_i = \underset{(0.0139)}{0.5697} - \underset{(0.0258)}{0.0058}\widehat{\Delta Earnings}_i + \underset{(0.0297)}{0.0219}\widehat{\Delta Emp}_i \quad (\text{N=1279, R}^2\text{=0.0007})$$

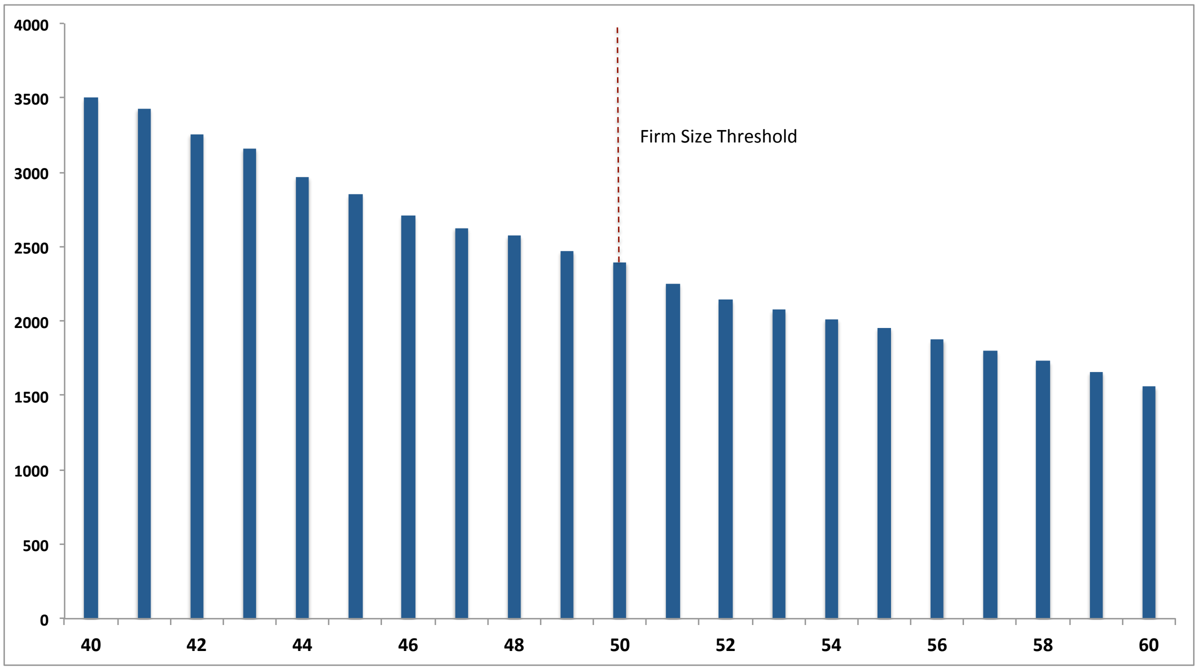
where again the pre-period growth rates are poor predictors of the size of the firm in which workers are employed.

A final concern is that to the extent that firms were able to anticipate the tax savings, we might expect that firms near the employment threshold would have adjusted their hiring behavior in order to fall just below the threshold, thereby qualifying for the tax write-off. Figure 1 plots the firm size distribution for the universe of U.K. firms, drawn from the U.K. Business Structure

[19] Again, note that this was by design since this was the basis for our choice of firm size window.

[20] Note that this is a stronger test relative to the comparison of individual growth rates since the regression approach tests for joint significance of the variables.

Figure 1: Firm Size Distribution



Notes: The figure shows the number of U.K. firms by firm employment, drawn from the universe of firms in the BSD. The size-threshold for "small" firms according to the official HMRC definition is indicated.

Database (BSD), in which each value reflects the mean number of firms across treatment period years for a given firm size.[21] First, we see the expected inverse relationship between size and firm density. Furthermore, the distribution suggests that there is no bunching of firm size just below the 51 employee threshold, suggesting that firms did not manipulate their size in order to receive the tax benefit. We therefore set aside this concern throughout.[22]

4.1.2. Firm Estimates

We begin our analysis of the tax inventive's impact on ICT investments by exploiting information from the QCES, which provides separate measures of firm investment in computer hardware, software and other ICT. Unfortunately, these detailed data are only available for the period after

[21]Note that the BSD contains the universe of all UK firms.

[22]To address this concern even further we ran all our analyses excluding firms between 48-50 employees. If firms were indeed manipulating their workforce to gain eligibility to the tax incentive, we would expect them to be within that size range. None of our results presented below are affected by this sample restriction and we therefore don't report these results here. However, the results are available upon request.

Table 2: Treatment Period Comparison of ICT Investment, 2000-2004

	Treatment Group (40-50)			Control Group (51-60)			Difference	
	Obs.	Mean	S.E.	Obs.	Mean	S.E.	Diff.	t-Stat.
Computer Hardware ('000 $)	5803	2.50	0.33	5521	3.53	0.41	-1.04	-1.99
Computer Software ('000 $)	5803	1.48	0.30	5521	1.49	0.24	-0.010	-0.02
Other ICT ('000 $)	5803	14.35	2.27	5521	12.51	1.40	1.83	0.65
Growth in Computer Hardware	3655	0.077	0.112	5521	0.031	0.046	0.046	25.88
Growth in Computer Software	3655	0.036	0.070	5521	0.014	0.049	0.022	14.03
Growth in Other ICT	3655	0.066	0.133	5521	0.026	0.045	0.040	17.47
Growth in Aggregate ICT Investment	3655	0.108	0.142	3109	0.067	0.088	0.041	14.20

Notes: The reported t-statistics are for a test of the treatment period difference in means between the treatment and control groups. Growth rates are average annual growth rates over the period.

2000, our treatment period. We therefore rely on the finding from Table 1 that plant and machinery investments, which include these components of ICT along with other capital investments, followed common trends in eligible and non-eligible firms prior to the introduction of the tax incentive.[23] Table 2 reports the treatment period (2000-2004) average annual growth in each ICT component for firms on either side of the size threshold. The results are quite stark and support the notion that the policy had an important impact. First, the treatment group's aggregate investment in computer hardware over the five year period (average annual growth rate $\times$ 5) was about 23 percent larger than the average for the control group, while computer software and other ICT investments were 11 percent and 20 percent higher, respectively. Each of these averages is very precisely estimated, as the t-statistics indicate. Finally, the aggregate relative increase in all ICT investment is estimated to be 20 percent. Based on these estimates, we interpret our results below for workers as being driven by policy-induced expenditure on computer hardware and other ICT.

Since we have data on plant and machinery investments (via the ARD) for both before and during the treatment period, we can generate additional evidence on the effect of the tax incentive using a difference-in-differences approach, which adopts the common pre-treatment trends as a counterfactual. Formally, we estimate the following regression over the period 1997 to 2004,

[23]While we feel it is unlikely, it is in principle possible that the ICT components followed divergent trends individually, but when aggregated to the level of plant and machinery the trends were the same. Unfortunately, this is a possibility that we cannot test for the pre-treatment period. However, Table 2 shows that individual and aggregate trends were going in the same direction during the treatment period within both size groups. It is thus unlikely that these trends were divergent in the pre-treatment period.

reporting the results of several different specifications that attempt to control for potential confounding trends:

$$\ln Y_{it} = \alpha_0 + \alpha_1 SMALL_i + \alpha_2 TI_t + \beta\left[SMALL_i \times TI_t\right] + \gamma' X_{it} + \epsilon_{it}, \tag{4}$$

where $SMALL_i$ is an indicator equal to 1 if firm i employs between 40 and 50 workers during the treatment period and is 0 otherwise (when employment lies between 51 and 60), TI_t is an indicator equal to 1 if year t is within the period 2000 to 2004 and is 0 otherwise (for years 1997 to 1999), and ϵ_{it} is a disturbance term for which we assume $E[\epsilon_{it}] = 0$. The key coefficient of interest is on the interaction $SMALL_i \times TI_t$, as it captures the differential impact of the policy within eligible firms relative to the control group. We cluster standard errors at the group level and the dependent variable is the log of plant and machinery investment as described in Section 3.

We further include X_{it}, which is a vector of control variables. Our baseline specification, reported in the first column of Table 3, includes year fixed effects (and drops the period dummy) as well as contemporaneous firm-level controls for employment and log labor productivity (gross value added per worker), each of which may reflect, or be proxies for, joint determinants of ICT investment and the likelihood of exploiting the tax incentive. Columns (1) to (3) cluster standard errors on firm employment. Our second specification adds sector fixed effects, the third adds group trends, the fourth clusters the standard errors on four-digit industry, and the final specification clusters on employment-year.[24]

Turning to the interpretation of the estimates in Table 3, we first note that each of the reported coefficients on the interaction terms in columns (1) through (5) is significant at the one or five percent level. Our preferred estimate in column (3) indicates that the "intent to treat" (ITT) effect of the tax incentive increased annual plant and machinery investment by 2.1 percent, on average,

[24] Again, we also repeated these regressions but removed firms with between 48 and 50 employees. The idea is that by doing so we account for the possibility that firms reduced their employment in the months prior to filing their tax documents in order to qualify for the incentive. Furthermore, it addresses the possibility that, to the extent that the incentive led to increased investment in ICT which then led to increased employment within the firm, the treatment may in fact push borderline firms over the size threshold, leading us to mistakenly classify them as large firms during the treatment period. This is likely to be a very minor effect given our estimates of the size of the employment effect, and indeed the results are virtually unchanged when removing this group of firms, so we do not report these results here. They are available upon request.

Table 3: The Average Effect of the Tax Credit on Investment

	Dependent Variable: Log Investment (Plant & Machinery)				
	(1)	(2)	(3)	(4)	(5)
$SMALL_f$	-0.0330***	-0.0296***	0.1680	0.1680	0.1680
	(0.0079)	(0.0057)	(2.6860)	(2.7670)	(2.7950)
$SMALL_f \times TI_t$	**0.0207*****	**0.0201*****	**0.0206****	**0.0206****	**0.0206****
	(0.0070)	(0.0063)	(0.0090)	(0.0101)	(0.0096)
Lab. Prod.	0.0018***	0.0012***	0.0012***	0.0012***	0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Employment	0.0020***	0.0020***	0.0020***	0.0020***	0.0020***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Obs.	27452	26661	26661	26661	26661
Clusters	Emp.	Emp.	Emp.	Ind.	Emp. x Year
Year FEs	Y	Y	Y	Y	Y
Sector FEs	N	Y	Y	Y	Y
Group Trends	N	N	Y	Y	Y

Notes: The table reports the results from estimating regression model (4) in which the dependent variable is investment in plant and machinery, as discussed in Section 3. Standard errors are reported in parentheses and are clustered on either the employment level (20 clusters, columns 1-3), detailed SIC industry (692 clusters, column 4), or employment by year (160 clusters, column 5). Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

relative to the control group. Given that, on average over the period 2000-2004, ICT investment constituted 21 percent of total plant and machinery investment, and assuming that the tax incentive had no impact on non-ICT investments, this translates to an approximate 10 percent average annual increase in ICT investment $\left({}^{0.021}/{}_{0.21}\right)$.[25] Note that this value is different from the magnitude indicated by the comparison of treatment and control group growth rates of aggregate ICT investment reported in Table 2 above (4.1 percent). This is not surprising given the lack of controls for pre-treatment trends in that exercise. Furthermore, the 10 percent figure due to the difference-in-differences exercise may overstate the true increase in ICT investment due to the policy to the extent that other components of plant and machinery investment also increased due to the policy, for instance if they are complementary with ICT capital.

Table 4 reports the results of our preferred specification (as in column (3) in Table 3) performed

[25]To be clear, the assumption is that the rise in plant and machinery investment that we observe is entirely due to an increase in ICT investment induced by the tax policy. If this is true, then we want to apply the 2.1 percent rise in investment to the 21 percent of plant and machinery that is ICT. This is the simple calculation we perform here.

Table 4: The Average Effect of the Tax Credit on Investment, by Sector

	Dependent Variable: Investment in Plant & Machinery							
	Agric., Fishing, Mining	Manuf-acturing	Whole-sale, Retail Trade	Cons-truction	Hotels, Resta-urants	Trans-port	Finance	Real Estate
$SMALL_f$	-18.5800	-0.1600	8.8380	-1.8920	-9.0240	-3.7540	7.7010	2.8930
	(16.8500)	(3.2330)	(11.6400)	(10.4400)	(5.7170)	(10.5700)	(12.9700)	(23.5200)
$\boldsymbol{SMALL_f \times TI_t}$	**0.0003**	**0.0075**	**0.0274***	**-0.0425**	**0.0006**	**0.0082**	**0.0267**	**0.0222**
	(0.0106)	(0.0045)	(0.0109)	(0.0353)	(0.0080)	(0.0094)	(0.0121)	(0.0156)
Lab. Prod.	0.0008***	0.0006***	0.0004***	0.0005***	0.0009***	0.0005***	0.0004***	0.0002
	(0.0003)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Employment	0.0016	0.0013***	0.0018**	0.0011*	0.0010***	0.0015**	0.0017**	0.0021
	(0.0011)	(0.0002)	(0.0007)	(0.0006)	(0.0004)	(0.0007)	(0.0008)	(0.0013)
Obs.	1543	13204	2131	2418	6259	2747	2139	1055
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Sector FEs	Y	Y	Y	Y	Y	Y	Y	Y
Group Trends	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table reports the results from estimating regression model (4) for eight broad UK sectors separately (without sector fixed effects). The dependent variable is investment in plant and machinery, as discussed in Section 3. Standard errors are clustered on detailed SIC industries (692 clusters) and are reported in parentheses below the coefficients. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

separately across eight broad UK sectors. While there is the suggestion of a positive effect in all sectors, though not always statistically significant, the strongest response to the tax incentive appears to have been in the wholesale and retail trade sector, followed by the financial sector. This pattern is consistent with the idea that ICT investments were made in order to replace back-office functions and to support the provision of services, and less so to support the production of goods. Autor et al. (2013a) also find evidence that recent investments in ICT have been biased toward these types of investments, following a period in the 1980s when ICT investments targeted the manufacturing process. These findings are also largely consistent with Corrado, Lengermann, Bartelsman and Beaulieu (2007), who look at the U.S. over the period 1995-2004 and find that the largest contribution of ICT capital to productivity growth occurred within the finance, high-tech, and distribution sectors.

Finally, we estimate a regression based on specification (4) in which the dependent variable is now a measure of labor productivity, namely gross value added per worker. The estimates indicate a four percent rise in labor productivity due to the policy-induced ICT investments. In

Section 4.2 we explore the extent to which these productivity gains accrued to different worker types within the firm.

4.1.3. Robustness of the Research Design

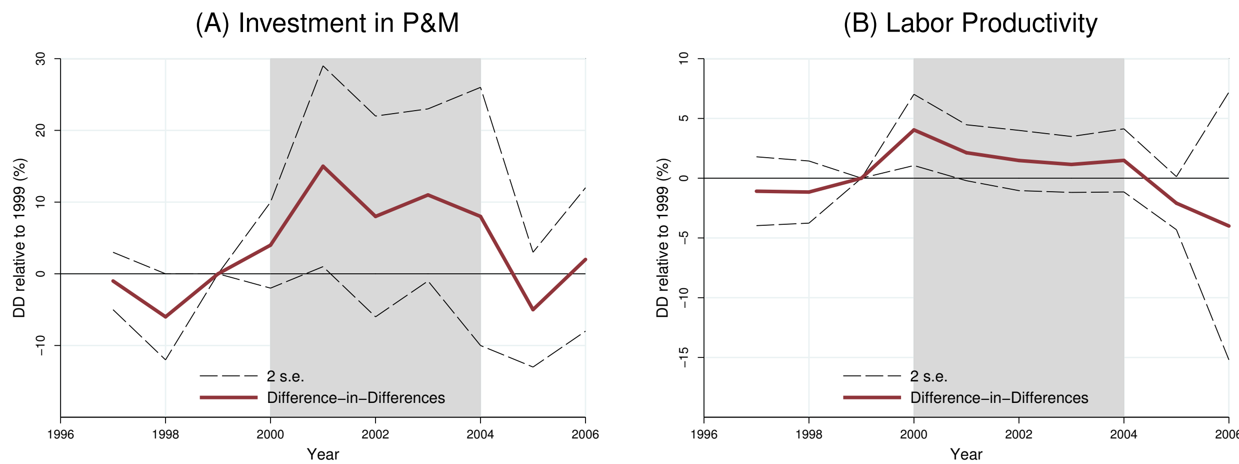
Since one of our key identifying assumptions is the absence of *differential trends* in the outcome variables (across small and large firms), we find it comforting that the addition of group specific time trends, as reported in column (3) of Table 3, has little effect on the estimated coefficients. However, given the importance of this requirement for our identification strategy, we conduct one additional test before turning to our main worker level analysis in the Section 4.2. Specifically, we consider the regression model

$$\ln Y_{it} = \nu_0 + \nu_1 SMALL_i + \sum_{\tau \in \mathbb{T}} \nu_\tau D_\tau + \delta_\tau \left[SMALL_i \times D_\tau \right] + \xi' X_{it} + \varepsilon_{it}, \tag{5}$$

where D_τ are time dummies for the years $\mathbb{T} = \{1997, 1998, 2000, \ldots, 2006\}$ and X_{it} is the vector of controls described above. Since we omit 1999, the year prior to the introduction of the tax incentive, the regression coefficients δ_τ capture the average *differential* percentage change in Y_{it} across small ($SMALL_i = 1$) and large ($SMALL_i = 0$) firms between year τ and the reference year, 1999. If our estimates reported in Table 3 were simply capturing systematic differential trends, then we would expect a stable, monotonic relationship between the coefficient estimates $\hat{\delta}_\tau$ and the time periods τ.

Figure 2 plots our estimates for these coefficients against τ, with the (omitted) reference coefficient δ_{1999} set equal to zero and the period during which the tax policy was in place highlighted in gray. The figure clearly illustrates a positive differential change since 1999 for each of the years during which the policy was in place. Moreover, the changes both before and after the policy period are close to zero, compared to the positive point estimates during the policy period. These patterns are in line with a differential impact of the tax policy that was confined to the treatment period.

Figure 2: Year-by-Year Difference-in-Differences Relative to 1999



Notes: The figures plot coefficient estimates $\hat{\beta}_\tau$ and corresponding two standard error bands based on regression model (5) for (A) investment in plant and machinery and (B) labor productivity. The coefficient estimates are reported in percent (%). The gray shaded area indicates the period during which the ICT tax incentive was in place.

4.2. The Impact of ICT on Labor Market Outcomes

The finding of a positive effect of the tax incentive on ICT investment is perhaps not surprising, particularly considering that it took place during a period in which ICT was becoming increasingly important to day-to-day business operations in the UK. In this section we go further and exploit the variation generated by these investments in order to estimate the short-run effect on the employment and wages of occupations with differing task content. Here we use data from the ASHE and repeat the difference-in-differences approach from the previous section using a modification of regression model (4) in which our dependent variables are now the log weekly wage and the log hours worked of each worker.

4.2.1. The Short-Run Effect of ICT on the Demand for Labor

We first note that the potential for confounding trends should be lessened due to the fact that, compared to firms, workers employed on either side of the firm-size threshold are more likely to be similar. It turns out that this is supported by the fact that the coefficients reported in Table 5 are relatively unchanged across specifications—i.e., the controls are relatively unimportant. Table 5 presents the results of specifications that progressively include controls for gender and age, sector

Table 5: Effect of ICT Investment on Wages and Employment

	(1)	(2)	(3)	(4)	(5)	(6)
A. Log Weekly Wage						
$SMALL_f$	-0.4310***	-0.0415***	-0.0412***	-0.8890	-0.8890	-0.8890
	(0.0067)	(0.0066)	(0.0067)	(2.3800)	(2.6130)	(2.6430)
$\boldsymbol{SMALL_f \times TI_t}$	**0.0215***	**0.0208***	**0.0201**	**0.0200**	**0.0200**	**0.0200**
	(0.0071)	(0.0072)	(0.0080)	(0.0082)	(0.0099)	(0.0094)
Age	0.0017***	0.0014***	0.0010***	0.0010***	0.0010***	0.0010***
	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Male	0.0003***	0.0003***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B. Log Hours Worked						
$SMALL_f$	-0.0155***	-0.0150***	-0.0149***	-0.0321	-0.0321	-0.0321
	(0.0024)	(0.0024)	(0.0024)	(0.8590)	(0.9430)	(0.9540)
$\boldsymbol{SMALL_f \times TI_t}$	**0.0077***	**0.0075***	**0.0073**	**0.0072**	**0.0072**	**0.0072**
	(0.0026)	(0.0026)	(0.0029)	(0.0029)	(0.0036)	(0.0034)
Age	0.0006***	0.0005***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Male	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obs.	27363	27363	26573	26573	26573	26573
Clusters	Emp.	Emp.	Emp.	Emp.	Ind. x Occ.	Emp. x Year
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Sector Fixed Effects	N	Y	Y	Y	Y	Y
Occupation Fixed Effects	N	N	Y	Y	Y	Y
Group Trends (small/large)	N	N	N	Y	Y	Y

Notes: The table reports the results from estimating regression model (4). The dependent variables are log weekly wages in panel A and log hours worked in panel B. As in the first stage regressions, we restrict the sample to workers employed by businesses with 40-60 workers. Standard errors are clustered on either the employment level (20 clusters, columns 1-4), detailed SIC industry by occupation (10,748 clusters, column 5), or employment by year (160 clusters, column 6). Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

fixed effects, group (small/large firm) trends, as well as a specification that adds occupation fixed effects.

Note that the inclusion of occupation fixed effects exploits the fact that each occupation is employed on both sides of the firm size threshold, and allows us to control for the fact that the occupational composition may differ between small and large firms, which may bias the estimates. Interestingly, the estimates do not change much with the inclusion of these fixed effects, indicating that the short-run effect of ICT is primarily a within-occupation effect. This finding is important in light of a recent debate in the literature about the relative importance of changes in the return *across* occupations versus *within* occupations in driving wage patterns over the past several decades. To some extent our findings reconcile these ideas since we find that within-occupation variation is important while, at the same time, we will show in Section 4.2.2 that there are two broad categories of occupations driving the results, non-routine cognitive and routine-cognitive occupations. This suggests that, within these broad categories, across-occupation variation may be relatively unimportant in the short run.[26]

From Table 5 we see that the ITT effect was to increase the average, annual wage by 2.0 percent (column (4) in panel A) and to increase the average number of hours worked by 0.7 percent (column (4) in panel B). Collectively, this suggests that the short-run, contemporaneous effect of an average, annual 2.1 percent increase in ICT investment (our estimated impact on firm investment from Table 3 above) was to increase the demand for labor on average. Given that average labor productivity increased by about four percent due to the tax incentive, the wage estimates suggest that workers captured about half of these gains. Furthermore, in line with the theoretical exercise in Section 2, the wage results indicate that ICT and non-routine labor are q-complementary.

Table 6 repeats the regression in column (4) of Table 5 for eight broad UK sectors allowing a comparison with the sector-specific results for firms in Table 4 above. As was the case for firms, the strongest results are in finance as well as wholesale and retail trade—an important result, as it provides strong evidence of the connection between the tax-induced firm ICT investment and worker outcomes, while again indicating that ICT investments were made in order to augment service provision rather than goods production. Moreover, this exercise also gives further confidence in our research design as we expect sectors in which we see no firm-investment effect to also show no effect on workers.

4.2.2. The Short-Run Effect of ICT on the Distribution of Labor Demand

In this section we estimate the effect of the policy on each of four occupation groups. Our organizing framework follows Acemoglu and Autor (2011), who classify occupations into four

[26]These results support the initial findings from Autor et al. (2003) who find a significant role for computers in explaining the variation in task content within occupations. Mishel, Shierholz and Schmitt (2013) also argue that within-occupation variation is key to explaining overall wage variation in recent decades. Note again that both of these studies are focused on long-run trends.

Table 6: Effect of ICT Investment on Wages and Employment, by Sector

	Agric., Fishing, Mining	Manuf-acturing	Whole-sale, Retail Trade	Cons-truction	Hotels, Resta-urants	Trans-port	Finance	Real Estate
A. Log Weekly Wage								
$SMALL_f$	5.0910	-1.9710	8.8050	0.0504	-6.4140	-0.8710	8.8050	-7.6410
	(12.6000)	(3.6150)	(11.1900)	(9.0250)	(5.1770)	(6.7010)	(11.8100)	(16.2300)
$\boldsymbol{SMALL_f \times TI_t}$	**0.0084**	**0.0063**	**0.1350*** **	**0.0359**	**-0.0009**	**0.0029**	**0.0842** **	**0.0150**
	(0.0080)	(0.0050)	(0.0517)	(0.0286)	(0.0073)	(0.0048)	(0.0342)	(0.0133)
Age	0.0007***	0.0005***	0.0004***	0.0005***	0.0008***	0.0007***	0.0004**	0.0003**
	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Male	0.0000	0.0001***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
B. Log Hours Worked								
$SMALL_f$	5.0910	-1.9710	8.8050	0.0504	-6.4140	-0.8710	8.8050	-7.6410
	(12.6000)	(3.6150)	(11.1900)	(9.0250)	(5.1770)	(6.7010)	(11.8100)	(16.2300)
$\boldsymbol{SMALL_f \times TI_t}$	**0.0561**	**0.0131**	**0.0911*** **	**0.0105**	**0.0092**	**0.0132**	**0.1090** **	**0.2910**
	(0.0535)	(0.0105)	(0.0349)	(0.0083)	(0.0728)	(0.0218)	(0.0442)	(0.2580)
Age	0.0007***	0.0005***	0.0004***	0.0005***	0.0008***	0.0007***	0.0001**	0.0001**
	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Male	0.0000	0.0001***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Obs.	2235	10745	2122	2795	6717	4855	2122	1720
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Occupation FEs	Y	Y	Y	Y	Y	Y	Y	Y
Group Trends	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table reports the results from estimating regression model (4) as in Table 5 for eight broad UK sectors (without sector fixed effects). The dependent variables are log weekly wages in panel A and log hours worked in panel B. We restrict the sample to workers employed by businesses with 40-60 workers. All regressions include a complete set of occupation fixed effects and group specific time trends. Standard errors are clustered on the employment level of the worker's firm and are reported in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

broad categories: (1) managerial, professional and technical occupations; (2) sales, clerical and administrative support; (3) production, craft, repair and operative occupations; and (4) service occupations. As Acemoglu and Autor (2011) argue, these categories are broadly representative of different sets of production tasks, namely (1) non-routine cognitive tasks; (2) routine cognitive tasks; (3) routine manual tasks; and (4) non-routine manual tasks, respectively. As noted in the introduction, several studies support the idea that this classification of occupations reflects important dimensions of computer-worker interaction (Autor et al., 2003, being the most prominent of

Table 7: Effect of ICT Investment on Routine and Non-Routine Workers

	Manual		Cognitive	
	Routine	Non-Routine	Routine	Non-Routine
	(1)	(2)	(3)	(4)
A. Log Weekly Wage				
$SMALL_f$	0.2020	0.0110	0.6890	0.9310
	(6.5210)	(6.4930)	(2.0140)	(2.0350)
$\boldsymbol{SMALL_f \times TI_t}$	**-0.0030**	**0.0124**	**-0.0050***	**0.0275***
	(0.0054)	(0.0228)	(0.0017)	(0.0089)
Age	0.0006***	0.0007***	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Male	0.0000	0.0000	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B. Log Hours Worked				
$SMALL_f$	0.2430	0.0133	1.5660	1.0080
	(7.8570)	(7.8230)	(4.5780)	(2.2030)
$\boldsymbol{SMALL_f \times TI_t}$	**-0.0036**	**0.0150**	**-0.0114***	**0.0298***
	(0.0065)	(0.0275)	(0.0039)	(0.0097)
Age	0.0008***	0.0008***	0.0018***	0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Male	0.0000	0.0000	0.0008***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Obs.	26630	26358	24001	23834
Year Fixed Effects	Y	Y	Y	Y
Sector Fixed Effects	Y	Y	Y	Y
Occupation Fixed Effects	Y	Y	Y	Y
Group Trends (small/large)	Y	Y	Y	Y

Notes: The table reports the results from estimating regression model (4) separately for the four broad occupation groups adopted in Acemoglu and Autor (2011).The dependent variables are log weekly wages in panel A and log hours worked in panel B. As in the first stage regressions, we restrict the sample to workers employed by businesses with 40-60 workers. All regressions include a complete set of occupation fixed effects. Standard errors are clustered on the employment level of the worker's firm and are reported in parentheses. Significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

these studies).

Table 7 presents the estimates, applying the specification from column (4) of Table 5 (incorporating the full range of controls and fixed effects, including occupation fixed effects) to these four occupation groups separately. The estimates differ significantly across occupation groups, though they present a consistent pattern with respect to both hours and earnings.

Specifically, columns (1) through (4) suggest that the overall gains in both employment and wages were by no means evenly shared across groups of workers performing fundamentally different tasks. In particular, the point estimates suggest that routine workers saw declines in hours and earnings, whereas non-routine workers gained on both fronts. Moreover, only the effects on *cognitive* occupations were statistically significant. In particular, our point estimates suggest a significant 2.8 percent increase in the wage and a 3.0 percent increase in hours worked, on average, for non-routine cognitive tasks and a simultaneous 0.5 percent decline in wages and a 1.1 percent decline in hours worked, on average, for routine cognitive tasks. Thus, the gains for non-routine (mostly cognitive) workers were several times larger than the losses for routine (mostly cognitive) workers. If we assume that the relative supply of task types over this period was fixed, these results imply a significant outward shift of the demand for non-routine cognitive work and a simultaneous, but less pronounced, inward shift in the demand for routine cognitive tasks. Furthermore, the estimates suggest an important economic impact—for instance, the wage estimate for non-routine cognitive workers implies an increase in income of about 50 pounds per month.

5. Concluding Remarks

Our short-run look at "what ICT does" refines the answer originally suggested by Autor et al. (2003). Consistent with their estimates, we find that the adoption of ICT leads to a rise in the demand for non-routine (mostly cognitive) tasks, even within a horizon of only five years. At the same time, we find only a modest tendency for ICT to replace routine work, and manual work seems mostly unaffected. We further find that over this period (2000-2004) computer investments were mostly concentrated in the retail and wholesale trade sector, with an important role for finance as well. This suggests that ICT plays an increasingly important role for services providers.

We implement a unique research design that exploits exogenous variation in ICT investments generated by a temporary tax incentive. While economists have long sought to identify the conditions under which tax incentives are effective in stimulating investment demand (at least since Hall and Jorgenson's (1967) seminal work) a clear consensus has yet to emerge from this debate.[27]

[27] For a few important contributions see Lucas (1976), Jorgenson and Yun (1990), Auerbach and Hassett (1991, 1992), Cummins et al. (1994, 1996), Goolsbee (1998), Chirinko et al. (1999), Cohen and Cummins (2006), as well as House and Shapiro (2008).

Most of the extant empirical work, even when exploiting natural experiments, takes a structural approach which often requires the approximation of many model quantities that are not directly observed in the data (e.g., firm- and asset-specific depreciation and tax rates, the rental rate of capital, etc.) and that are conditional on the particular structural assumptions. In contrast, our research design relies solely on two identifying assumptions, which are likely to be satisfied.

Our short-run estimates provide insight into the nature of technological change in part because they implicitly highlight differences between the short- and long-run impact. Specifically, the modest impact on routine workers reflected in our estimates suggests an asymmetry in the timing of the organizational change that goes along with ICT adoption. New technologies may demand immediate engagement by workers with the skill and ability to execute non-routine cognitive tasks. As a result, organizational change—i.e., hiring and firing, extending worker hours, restructuring of workplace hierarchies, etc.—aligns itself with this requirement in the short run. There is seemingly less of a need in the short run to replace workers who previously performed the routine tasks that are now performed by ICT—though, again, we do find evidence of some substitution. We also note that this asymmetry in timing is consistent with Jaimovich and Siu (2012), who find that about 92 percent of the routine jobs lost in the US since the 1980s were lost during a 12-month window following NBER dated recessions. This is despite the fact that aggregate investment is highly procyclical, and therefore most investment—including ICT investment—happens during booms rather than immediate recoveries from a recession.

Finally, one of the standard predictions from neo-classical investment demand theory is that investment tax breaks—or, for that matter, any policy-induced reduction in the current price of investment goods—are only effective in altering the *timing* of investment. In this case, they will only stimulate current investment demand if they are expected to be sufficiently temporary and if the eligible assets are sufficiently long-lived. While the UK tax incentive studied here was explicitly short-lived, ICT capital is among the fastest depreciating forms of equipment, with annual depreciation rates of up to 30 percent. In light of this, the success of the ICT tax incentive explored here is somewhat puzzling. Some possible explanations include: (1) the tax incentive was quite generous (a 100 percent tax write-off); (2) computer purchases represent relatively small capital investments and therefore require less financial planning; (3) in 2000, the "computer revolution" was well under way and managers may have felt pressure to invest in ICT capital. We leave further exploration of this puzzle to future research.

Overall, we view our evidence as a step toward a more nuanced understanding of how firms respond to the demands that new technologies place on the structure of employment within the firm.

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