IT AIN'T WHAT YOU DO IT'S THE WAY THAT YOU DO I.T. - TESTING EXPLANATIONS OF PRODUCTIVITY GROWTH USING U.S. AFFILIATES

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Abstract

Productivity growth in sectors that intensively use information and communication technologies (ICT) appears to have accelerated faster in the US than in Europe since 1995. If this was partly due to the superior management/organization of US firms (rather than simply the US geographical or regulatory environment) we would expect to see a stronger association of productivity with IT for US multinationals located Europe than for other firms. We examine a large panel of UK establishments from all business sectors and provide evidence that US owned establishments have a significantly higher productivity of IT capital than either non-US multinationals or domestically owned establishments. Indeed, the differential impact of IT appears to fully account for almost all the difference in total factor productivity between US-owned and all other establishments. Further, this finding is particularly strong in the sectors that intensively use information technologies: the very same ones that account for the US-European productivity growth differential since the mid 1990s.

Key words: *Productivity, IT, multinationals.*

JEL classification: *E22, O3, O47, O52*

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I. INTRODUCTION

One of the most startling economic facts of the last decade has been the reversal in the long-standing catch-up of European countries' productivity with the US. Labour productivity growth in the US accelerated after 1995 following a long-term slowdown after the 1970s Oil shocks. Decompositions of this productivity growth show that the great majority has occurred in those sectors that either intensively use or produce IT (information technologies)[1]. EU countries had similar productivity acceleration in IT producing sectors but failed to achieve the spectacular levels of productivity growth in the sectors that *used* IT intensively (e.g. O'Mahony and Van Ark, 2003). These sectors include retail, wholesale and financial intermediation. Britain has done better than France or Germany in this respect, but not as well as the US (e.g. Basu et al, 2003). Given the common availability of IT throughout the world at broadly similar prices, it is a major puzzle to explain why these IT related productivity effects have not been more widespread.

So why has there not been faster productivity growth in Europe since the mid 1990s? One explanation is simply differences in the way we measure productivity across countries (Blanchard, 2004). This is possible, but the careful work of O'Mahony and Van Ark (2003) and others who focus on the same sectors in the US and EU, use US style adjustments for hedonic prices, software capitalization and aggregate demand conditions, still find a difference. If the difference is real, then at least two explanations are possible. First, there are some "natural advantages" to the environment in which US plants operate that enables them to take better advantage of the opportunity of rapidly falling IT prices. These natural advantages could be tougher product market competition, lower regulation in the product and labour markets, better access to risk capital, more educated workers, a larger size of market, more geographical space or a host of other factors. A second class of explanations stresses that it is not the US environment *per se* that matters but rather the internal organization (the depth of "organizational capital") of US firms that has enabled better exploitation of IT. For

[1] See, for example, Stiroh (2002a). Jorgenson (2001), Oliner and Sichel (2001). In the 2002-2004 period preliminary findings in Oliner and Sichel (2004) find that the US productivity growth remained strong, but there was a more widespread increase in productivity growth across sectors.

example, US firms may be simply better managed or they have adopted features that are better at exploiting IT (e.g. more decentralization or flatter hierarchies)[2].

One way to test between the "US environment" and the "US organization" hypotheses is to examine the IT performance of US owned organizations in a non-US environment. Assuming that US multinationals export their business models outside the US – and a walk into McDonalds or Starbucks anywhere in Europe suggests that this is not an entirely unreasonable assumption – then analyzing the IT performance of US multinational establishments in Europe should be informative. (We return to the origins of differences in European vs. US organizational forms in the conclusion).

In this paper we examine the productivity of IT in a panel of establishments located in the UK, examining the differences in IT intensity and productivity between plants owned by US multinationals, plants owned by non-US multinationals and domestically owned plants. The UK poses a useful testing ground because (a) it has not experienced a US-style productivity acceleration since 1995 (as Basu et al (2003) show) and (b) it is a large recipient of foreign direct investment so we are able to compare across many types of ownership. A key comparison group for US multinationals are "statistically similar" non-US multinationals (i.e. establishments in the same industry, of a similar age, size and factor intensity). We report some evidence that the key difference in understanding productivity differences is the ability of US multinationals to gain a higher return to IT than non-US multinationals (and domestic plants). This effect is strongest in precisely those industries that experienced the largest relative productivity gains in the US after 1995 (the sectors that intensively used IT). This finding is robust to a number of tests for omitted variables, the possible endogeneity of IT, and US firms' "cherry picking" UK plants (we look before and after US takeovers compared to non-US takeovers). In short, we conclude that the higher productivity of IT in the US is not just the US environment, but also ahs something to do with the internal organization of US firms.

Our paper relates to several literatures. First, there is a large literature on the impact of IT on productivity, but most of this is based on data aggregated to the industry or macro-economic

[2] Bresnahan, Brynjolfsson and Hitt (2002) and Caroli and Van Reenen (2001) both find that internal organisation

level. Even the pioneering work of Brynjolfsson[3] and his co-authors focuses at the firm level which may conceal much heterogeneity between plants *within* firms. In this paper we provide, for the first time, estimates for the level and the returns to IT capital stocks for a panel of around 11,000 establishments, probably the largest micro-based sample in the world for this kind of exercise. Our database, unlike the US LRD, also covers the non-manufacturing sector, which is important as the majority of sectors that use IT intensively are in services.

Second, in a reversal of the Solow Paradox, the firm level productivity literature has found returns to IT that are *larger* than one would expect under the standard growth accounting assumptions. Brynjolfsson and Hitt (2003) argue that this is due to complementary investments in "organizational capital" that are reflected in the coefficients on IT capital. Almost all of these studies are on US firms, however, and the data used is generally prior to the post 1995 acceleration in productivity growth. Examining UK firms that may have made fewer complementary investments we might expect to see lower returns (Basu et al, 2003).

Thirdly, there is a literature on the productivity of multinationals compared to similar non-multinational establishments. The first wave of research that compared domestically owned plants with multinationals was clearly misleading as multinationals are a self-selected group that have some additional efficiency as signaled by their ability to operate overseas. But comparing across different multinationals it appears that US plants are more productive whether based geographically in the US (Doms and Jensen, 1998) or in other parts of the world such as the UK (e.g. Criscuolo and Martin, 2005). Our paper suggests that a major reason for this is the way in which US multinationals are able to use new technologies more effectively than other multinationals[4].

In summary, we do find significant impacts of IT on productivity. We also find that we can account for almost all of the higher productivity of US multinationals by the higher productivity impact of their use of IT. Furthermore, this US advantage is strongest in the

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and other complementary factors such as skills are important in generating significant returns to ICT.

[3] Brynjolfsson and Hitt (1995, 2003), Bresnahan, Brynjolfsson and Hitt (2002), Brynjolfsson,Hitt and Yang (2002). Brynjolfsson and Yang (1996) or Stiroh (2002b) survey the evidence.

[4] We do not focus in this paper on whether FDI creates positive productivity spillovers (see Haskel, Pereira and Slaughter, 2002, for evidence on this). This is because we do not find any evidence for the existence of spillovers from IT in general in our data.

sectors that intensively use IT: precisely those sectors that account for the faster productivity growth in the US than Europe since 1995. This suggests that at least some of the differential performance of productivity between the US and the EU since the mid 1990s is due to the internal organization of US firms. Drawing on some of our other work we show that there is evidence for significant differences in the "organizational capital" of US firms relative to British and other European firms, even when these US firms operate in Europe.

The structure of this paper is as follows. Section II discusses the econometric strategy and section III the data. Section IV gives the main results, Section V some interpretation and section VI offers some conclusions.

II. MODELLING STRATEGY

Following Klette (1999) establishments in an industry are assumed to be constrained by a production function $Q_{it} = A_{it} F_t(X_{it})$ where Q is gross output of establishment i at time t, A_{it} is an establishment specific productivity factor and $F_t(.)$ is a part of the production function common to all plants. The production function relationship can be expressed in terms of logarithmic deviations from a point of reference[5]. This reference point can be thought of as the representative plant's level of output and inputs for each year. Rewriting the production function in terms of logarithmic deviations from this reference point (denote such a transformed variable $\tilde{x}_{it} \equiv \ln X_{it} - \ln X_t$ where X_t is the reference point[6])

$$\tilde{q}_{it} = \tilde{a}_{it} + \alpha_{it}^M \tilde{m}_{it} + \alpha_{it}^L \tilde{l}_{it} + \alpha_{it}^K \tilde{k}_{it} + \alpha_{it}^C \tilde{c}_{it} \qquad (1)$$

where C is the IT capital stock of computer hardware, K is non-IT capital, L is labour, M is materials and a lower case letter denotes a natural logarithm ($x = lnX$, etc). The α_{it}^j is the output elasticity for factor j evaluated at an internal point between X_{it} and X_t.

[5] This uses a version of the multivariate generalized mean value theorem (e.g. Thomas, 1968). The production function is therefore much more general than simply Cobb-Douglas.

[6] We will generally use the four digit industry mean at time t as the reference point for x_t, but we also used alternatives such as the median plant in the same four digit industry in the same year.

We are particularly interested in the role of IT capital and whether the impact of computers on productivity is systematically higher for the plants belonging to US firms in the sectors that intensively use IT and that appear to have been responsible for the bulk of the US productivity acceleration since the mid 1990s. Consider parameterizing the output elasticities in equation (1) as:

$$\alpha_{it}^{J} = \alpha_{h}^{J,0} + \alpha_{h}^{J,USA} D_{it}^{USA} + \alpha_{h}^{J,MNE} D_{it}^{MNE} \tag{2}$$

where D_{it}^{USA} denotes that the establishment is owned by a US firm in year *t* and D_{it}^{MNE} denotes that the establishment is owned by a non-US multinational enterprise (the base case is that firm is a non-multinational purely domestic firm). The sub-script *h* denotes sector (e.g. industries that use IT intensively vs. non-IT intensive sectors) and the super-script *J* indicates a particular factor of production (*M, L, K, C*). We further assume that total plant specific efficiency can be written as:

$$\widetilde{a}_{it} = a_i + \delta_h^0 + \delta_h^{USA} D_{it}^{USA} + \delta_h^{MNE} D_{it}^{MNE} + \gamma_h{}' \widetilde{z}_{it} + u_{h,it} \tag{3}$$

where *z* are other observable factors influencing productivity such as establishment age, region, whether the establishment is part of a multi-plant group, etc. So the general form of the production function that we will estimate is (combining equations (1) through (3)):

$$\begin{aligned} \widetilde{q}_{it} = & \sum_{M,L,K,C \in J} \alpha_h^{J,0} \widetilde{x}_{it}^J + \sum_{M,L,K,C \in J} \alpha_h^{J,USA} D_{it}^{USA} \widetilde{x}_{it}^J + \sum_{M,L,K,C \in J} \alpha_h^{J,MNE} D_{it}^{MNE} \widetilde{x}_{it}^J \\ & + a_i + \delta_h^{USA} D_{it}^{USA} + \delta_h^{MNE} D_{it}^{MNE} + \delta_h^0 D_{it}^0 + \gamma_h{}' \widetilde{z}_{it} + u_{h,it} \end{aligned} \tag{4}$$

where $x^M = m$, etc.

Note that although we will estimate equation (4) in some specifications, most of the interactions between factor inputs and ownership status are insignificantly different from zero. One interaction that will stand out is that between the US ownership dummy and IT capital: the coefficient on computer capital is significantly higher for US firms than for other multinationals and/or domestic firms. Consequently our preferred specifications are usually of the form:

$$\begin{aligned}\tilde{q}_{it} &= \alpha_h^M \tilde{m}_{it} + \alpha_h^L \tilde{l}_{it} + \alpha_h^K \tilde{k}_{it} + \alpha_h^{C,0} \tilde{c}_{it} + \alpha_h^{C,USA} D_{it}^{USA} \tilde{c}_{it} + \alpha_h^{C,MNE} D_{it}^{MNE} \tilde{c}_{it} \\ &+ a_i + \delta_h^{USA} D_{it}^{USA} + \delta_h^{MNE} D_{it}^{MNE} + \delta_h^0 D_{it}^0 + \gamma_h' \tilde{z}_{it} + u_{h,it}\end{aligned} \tag{5}$$

where the key hypotheses are whether $\alpha_h^{C,USA} D_{it}^{USA} = 0$ and/or $\alpha_h^{C,USA} D_{it}^{USA} = \alpha_h^{C,MNE} D_{it}^{MNE}$.

Under the assumptions of perfectly competitive factor input markets and product markets, in the long-run the parameters on each factor input will be equal to their share of revenue. Under these assumptions, standard growth accounting exercises can be performed. Denote the factor share of *J* as s_{it}^J

$$s_{it}^J = \left(\frac{W_{it}^J X_{it}^J}{P_{it} Q_{it}} \right) \tag{6}$$

where W^J is the factor price of input X^J.

Of course, these are very strong assumptions so it is of interest to estimate equations (4) and (5) directly and see whether "normal returns" hold in practice to all factors. In particular, we are interested in whether there may be larger than expected coefficients on IT capital, particularly for US owned establishments.

An alternative to estimating equation (4) is to consider a TFP based specification. We consider "measured TFP" in differences, Δ_dMTFP

$$\Delta_d MTFP = \Delta_d \tilde{q}_{it} - \bar{s}_{it}^M \Delta_d \tilde{m}_{it} - \bar{s}_{it}^L \Delta_d \tilde{l}_{it} - \bar{s}_{it}^K \Delta_d \tilde{k}_{it} - \bar{s}_{it}^C \Delta_d \tilde{c}_{it} \tag{7}$$

where *d* is the order of differencing (e.g. *d* = 1 implies first differences, *d* = 2 second differences and so on). A bar denotes that the shares are averaged (e.g. the unweighted average of this year's share and last year's share)[7].

[7] In order to reduce the influence of measurement error at the establishment level we experimented with several ways of constructing the factor shares. An alternative to (6) is using the industry specific medians by ownership type. See Griffith, Redding and Van Reenen (2004) for a discussion over various ways of measuring TFP.

We consider estimating in first or longer differences specifications similar to Brynjolfsson and Hitt (2003). In the context of equation (5) this becomes:

$$\begin{aligned}\Delta_d MTFP_{it} &= b_h^0 \Delta_d \tilde{c}_{it} + b_h^{USA} \Delta_d (D_{it}^{USA} \tilde{c}_{it}) + b_h^{MNE} \Delta_d (D_{it}^{MNE} \tilde{c}_{it}) + \\ &\delta_h^{USA} \Delta_d D_{it}^{USA} + \delta_h^{MNE} \Delta_d D_{it}^{MNE} + \delta_h^0 \Delta_d D_{it}^0 + \gamma_h ' \Delta_d \tilde{z}_{it\,i} + \Delta_d u_{h,it}\end{aligned} \tag{8}$$

Under the null of normal returns then all the coefficients on IT capital should be zero ($b_h^0 = b_h^{USA} = b_h^{MNE}$) since $b_h = (\alpha_{it}^C - s_{it}^C)$, etc.

In all specifications we allow for a general structure of the error term that allows for arbitrary heteroskedacity and autocorrelation over time. But there could still be establishment specific unobserved heterogeneity. So we also consider also including a full set of establishment level fixed effects (the "within groups" estimator). The fixed effects estimators are more rigorous as there may be many unobservable omitted variables correlated with IT that generate an upwards bias to the coefficient on computer capital. On the other hand, attenuation bias (caused by measurement error in IT and other right hand side variables) will be exacerbated by including fixed effects generating a bias towards zero[8].

We also want to allow for endogeneity of the factor inputs and take several approaches to dealing with this issue. Our preferred measure is to use the "System GMM" estimator of Blundell and Bond (1998) but we also compare this to a version of the Olley Pakes (1996) estimator. We also consider some "external" instruments for IT, in particular changes to the tax regime surrounding IT and the spread of access to Broadband. These methods are detailed in Appendix A.

III. DATA

A full description of the datasets used is in Appendix B. Our base dataset is a panel of establishments covering almost all sectors of the UK private sector called the ABI. This underlies many of the UK national statistics and is similar in structure to the US Longitudinal

[8] See Griliches and Mairesse (1998) for a general discussion of this problem with production functions and Brynjolfsson and Hitt, 1995, 1996, 2003) for a discussion specifically on IT.

Research Database (LRD) being a population sample of large plants and a stratified random sample of smaller plants. Unlike the LRD the ABI also covers the non-manufacturing sector from the mid 1990s onwards. This is important as the majority of the sectors that intensively use IT are outside manufacturing.

The response rates to the ABI are high because it is illegal not to return the forms to the Office of National Statistics (ONS). The ABI contains all the basic information needed to estimate production functions (gross output, labour, materials, investment, etc.). The Office of National Statistics also conducts supplementary surveys that can be used to estimate IT capital expenditure on hardware which we matched into the ABI.

We build up IT capital stocks from the IT expenditures using the perpetual inventory method following Jorgenson (2001) keeping to US assumptions over depreciation rates and hedonic prices. We report several ways of dealing with the problem of initial conditions[9]. Our dataset runs from 1995 through 2003, but there are many more observations in each year post 1999. After cleaning we are left with 22,736 non-zero observations.

Some descriptive statistics are in Tables 1 and 2. There are many small and medium sized establishments in our sample - the median establishment employs 238 workers and the mean establishment employs 796. We lose some of the smallest plants because the surveys use stratified random sampling which gives higher sampling weights to the larger establishments in the economy. Median output per worker (our main measure of productivity) is £81,080 and value added per worker is £28,260. The mean IT capital in the plant is just under £1million. At rental prices average IT capital is about 1% of gross output at the unweighted mean (1.5% if weighted by size) or 2.3% of value added. These are similar to the economy wide means in Basu et al, 2003, which is reassuring for the representativeness of the sample).

[9] Essentially we exploit the fact that we have a long time series of industry level estimates of IT flows and stocks from other studies that use the input-output matrices (e.g. O'Mahony and Van Ark, 2003 ; Oulton and Srinivasan, 2004 ; Basu et al, 2003). We impute an estimate of an establishment's initial IT stock based on its observed flow of IT expenditure and the industry information. Because we have a short time series for many firms we are careful to check the robustness of the results for different assumptions over the treatment of the inital year of the IT stock. We consider different ways to impute the initial value, and also show below that using just the flow measures (i.e. not using any imputations for the initial year) gives us qualitatively similar results.

Table 2 gives some characteristics of plants by ownership type: US multinationals ("US"), non-US multinationals ("MNE") and domestic establishments ("UK"). We express all these variables in deviations from their four digit industry means. Notice that we have a large numbers of multinational establishments in the sample: about 8% of establishments are US owned, 29% are non-US owned and 63% are purely domestic. This understates the importance of multinationals as their share of employment is higher and their share of output higher still. US establishments have about 50% more employees than the industry average which is similar to the non-US multinationals who have 46% more employees than the average. In terms of value added per worker US multinationals are 23% more productive and non-US multinationals are 16% more productive than the industry average (domestic plants are about 11% less productive). In terms of output per worker the US advantage is 21.5% and non-US advantage is 17.5%. This is consistent with evidence that the plants of multinational US firms are more productive whether or not the plants are based on US soil or foreign soil[10].

Table 2 also shows that the US productivity advantage is partially linked to greater use of inputs: US plants use about 10% more materials/intermediate inputs and 4% more non IT capital than non-US multinationals. But the final column shows that IT capital may also be a very important factor: US firms use 40% more IT capital per worker than average whereas non-US multinationals use only 20% more. This is a very substantial difference and the econometric work below investigates to what extent differential IT expenditure accounts for any US productivity differences (we will show it accounts for some of the difference, but far from all).

IV. RESULTS

IV.A Basic Results

The first basic production function results are contained in Table 3. The first three columns present OLS results, the next three columns present GMM-system results and the final column presents Olley Pakes results. Column (1) presents the results without fixed effects, but all other columns control for fixed effects. Across all specifications, all the factor inputs, including IT capital are positive and significant. In column (1) the sum of the coefficients on

[10] On the former see Doms and Jensen (1998) on the latter see Criscuolo and Martin (2005), Griffith (2001),

the factor shares is 0.99, very close to constant returns to scale. Column (2) includes a full set of 11,000 establishment specific fixed effects. The coefficients all remain significant at conventional levels. The coefficient on IT capital falls from 0.04 to 0.03, the coefficient on materials falls from 0.54 to 0.47. By contrast the coefficient on non-IT capital increases from 0.12 to 0.16 and the coefficient on labor rises from 0.29 to 0.32. Compared to many other results in the micro production function literature[11] the results here are reasonably stable when including fixed effects[12].

To implement our GMM estimates we need to condition on a sample where we have at least three continuous time series observations (the OLS estimates keep all observations, even if we only observe a plant for a single period). Column (3) conditions on the same sub-sample that we will estimate our GMM results on and re-runs the within groups estimate of column (2). The estimates are stable even after throwing away about three quarters of the sample. Column (4) presents the equivalent specification using GMM-SYS. The absence of higher order serial correlation and the failure of the Sargan test to reject are consistent with the hypothesis that the instruments are valid. The coefficients on materials and non-IT capital fall and the coefficients on labour and IT capital rise compared to column (3). Column (5) implements a general dynamic model including lags of all the independent variables and the dependent variable. We then impose the common factor restrictions by minimum distance and present these restricted estimates in the final column (note that we cannot reject the COMFAC restrictions as indicated by the diagnostics at the base of column (6)). The coefficient on IT (and the other factors) remains positive and significant with a coefficient of about 0.04 (similar to OLS levels in fact). Finally, column (6) implements a version of the Olley Pakes method. Although all the variables are significant at conventional levels this produces the lowest coefficient on IT capital in Table 3: 0.02.

Overall the different estimators produce estimates of the elasticity of output with respect to IT in the range of 0.02 to 0.04. It is reassuring to find that productivity does indeed have a positive and significant association with IT capital, consistent with the findings from the new

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Griffith, Simpson and Redding (2002).

[11] Griliches and Mairesse (1997), Olley and Pakes (1996) or Levinsohn and Petrin (2003)

[12] The transformation of variables into deviations from the industry mean helps stability and it may be that there is much less measurement error in this mandatory establishment survey than the typical firm study using accounting data.

micro studies in the US and elsewhere. Although the coefficient is larger than the share of IT capital in output (which is about 1% to 1.5% in Table 1) the difference is not as dramatic as has been found in other studies such as Brynjolfsson and Hitt (2003)[13]. We will discuss possible reasons for this below, but an obvious reason is that IT impacts may be heterogeneous between US firms and non-US firms.

We considered several experiments changing our assumptions concerning the construction of the IT capital stock. Most of these are detailed in the Appendix. First, there is uncertainty over the exact depreciation rate for IT capital, so we experimented with a number of alternatives including the extreme case of 100% depreciation and just working with the flows. Secondly, we do not know the initial IT capital stock for ongoing firms the first time they enter the sample. Our base method is to assume that the IT investment rate is the same as the industry average IT investment rate in the base period. An alternative is to assume that the plant's share of the IT stock is the same as its share of employment in the industry in the base period. Appendix Table 2 shows that this affects the magnitude of the coefficient on IT, but it always remains positive and significant.

IV.B. US Multinationals, IT and productivity

Table 4 contains the key results of our test of whether the productivity advantage of US multinationals is linked to the use of IT. Column (1) estimates the basic production function from column (2) of Table 3 but includes a dummy variables for whether or not the plant was owned by a US multinational ("USA") or a non-US multinational ("MNE") with plants who are domestically owned being the omitted base. US establishments are 8.5% more productive than UK domestic establishments and non-US multinationals are 4.8% more productive. The difference between the US and non US MNE coefficients is also significant at the 5% level (p-value =0.001).

[13] There are a number of possible reasons for the differences. Most obviously, Brynjolfsson's data is from the US whereas ours is from the UK- we show that there appears to be larger IT coefficients for US firms than for UK firms. Other differences include (a) we are using more disaggregated data (establishments rather than worldwide accounts of firms); (b) our measure of IT capital is constructed in the standard way from flows of expenditure whereas BH use a measure based on pricing different pieces of IT equipment; (c) our sample is much larger and covers a more recent time period (d) our estimation techniques are different. We investigate some of these below.

The second column of Table 4 includes the IT hardware measure which enters significantly and reduces the coefficients on the ownership dummies. US plants are more IT intensive than other plants (see the earlier discussion of Table 2) and this explains some of the productivity gap. But it only accounts for about 12% of the initial gap, i.e. about one percentage points of initial 8.5% productivity gap ((0.085-0.075)/0.085). Column (3) includes two interaction terms: one between IT capital and the US dummy and the other between IT capital and the non-US multinational dummy. These turn out to be very revealing. The interaction between the US dummy and IT capital is positive and significant at conventional levels. According to column (3) doubling the hardware stock is associated with an increase in productivity of 5.2% for a US MNE but only 4.1% for a domestic firm. Non-US multinationals are insignificantly different from domestic UK firms in this respect: we cannot reject that the coefficients on IT are equal for domestic UK firms and non-US multinationals. It is the US firms that are different. In fact, the linear US dummy is now insignificantly different from zero. Interpreted literally, this means that we can "account" for all of the US MNE advantage by their superior use of IT. Hypothetically, US plants that have less than about £1,000 of IT capital (i.e. $\ln(C) = 0$) are no more productive than their UK counterparts (no US plants in the sample have IT spending this low, of course).

To investigate the industries that appear to account for the majority of the productivity acceleration in the US we split the sample into "highly IT using intensive sectors" in column (4) and "low IT using intensive sectors" in column (5). Sectors that use IT intensively includes retail, wholesale and printing/publishing – see Appendix Table 1 for a full list. The US interaction with IT capital is much stronger in the IT intensive sectors, being insignificantly different from zero in the less IT intensive sectors (even though there are twice as many firms in these industries). The final three columns include a full set of establishment fixed effects. The earlier pattern of results is repeated with a higher value of the interaction than in the non-fixed effects results. In particular, column (7) demonstrates that US plants have significantly higher productivity of their IT capital stocks than domestic firms or other multinationals. A doubling of the IT capital stock is associated with 2% higher productivity for a domestic plant, 2.5% for a non-US multinational but 5% higher productivity for a plant owned by a US multinational.

A criticism of Table 4 is that we only allow the coefficient on IT to differ by ownership type. Table 5 allows all coefficients to differ by estimating the production function separately for different ownership types. In Panel A of Table 5 we present results for the IT intensive sectors and in Panel B we present results for the non-IT intensive sectors. Column (1) presents results for just US firms, column (2) for all firms except the US and column (3) for non-US multinationals only. Looking at the coefficient on hardware the usual pattern is observed- the coefficient is almost twice as large for the US firms (0.051) as for all firms except the US (0.027). The base of the Table presents a formal Chow test of the restricted model (where all coefficients are restricted to be the same across sub-samples) against the unrestricted models (columns (1) and (2)). We reject the restrictions at the 1% level. The test may be seen as weak as column (2) also includes domestic firms so a tougher test is whether the US firms are different from other multinationals. Column (3) presents results for non-US multinationals and shows, as expected, a coefficient on IT capital lower than the US multinationals in column (1) but higher than the domestic firms. Nevertheless, the F-Test again rejects the restriction of the equality of coefficients at the 1% level

Panel B of Table 5 repeats this exercise for non-IT intensive sectors. The equivalent F-tests at the base of the panel show that we cannot reject the hypothesis that the coefficients are equal across the sub-samples whether we compare US firms to all other firms or simply to other multinationals.

Table 6 presents a series of robustness tests on the main results - we focus on the fixed effects specification in the IT intensive sectors which are the most demanding specifications. The first column represents our baseline results from column (7) in Table 4. Column (2) simply re-iterates what we have already observed in Table 4 by estimating the production function with a full set of interactions between the US dummy and the factor inputs. None of the additional non-IT factor input interactions are individually significant and the joint test at the base of the column of the additional interactions shows that they are insignificant (for example the joint test of the all the US interactions except the IT interaction has a p-value of 0.76). We cannot reject the specification in column (1) as a good representation of the data against the more general interactive models of Table 4.

The third column of Table 6 implements an alternative way of examining whether IT returns are higher for US multinationals by aggregating IT and non-IT capital into total capital and including an additional variables for the proportion of IT capital in the total capital stock and its interactions with the ownership dummies. All terms are positive and the US interaction with IT is significantly different from zero at the 1% level. Another concern is that the US*IT interaction reflects some other non-linearity in the production function. We tried including a much fuller set of interactions and higher order terms, but these were insignificant. Column (4) shows the results of including all the pairwise interactions of materials, labour, IT capital and non-IT capital and the square of each of these factors. The additional terms are jointly insignificant (p-value = 0.32) and the US interaction with IT remains basically unchanged. Column (5) presents a value added based specification instead of an output based specification. The results are similar to using gross output (although the coefficients are larger of course).

A possible explanation for the higher productivity of IT in US firms is that US multinationals may tend to set up plants in specific industries in which the returns to IT are particularly high. The interaction of IT capital with the US dummy would then capture omitted industry characteristics rather than a "true" effect linked to US ownership. To test for this potential bias we included in our regression as an additional control the percentage of US multinationals in the specific four digit SIC industry ("USA_IND")[14]. We also construct a similar industry level variable for the non-US multinationals ("MNE_IND"). There is no evidence that IT returns are apparently higher in sector with a larger US MNE presence (see column (6)).

Next, we considered the role of skills. Our main control for labour quality in Table 3 is the inclusion of establishment specific effects which, so long as the labour quality does not change too much over time, should control for the omitted human capital variable. As an alternative we matched in education information at the industry-region level from an individual level survey, the Labor Force Survey[15]. In the specifications without fixed effects,

[14] The variable is constructed as an average between 1995 and 2003 and is built using the whole ARD population.

[15] The skills measure is the proportion of workers in a two digit industry who had a college degree from the LFS (Labor Force Survey) separately for each year and region (see Data Appendix)

there was some evidence for a positive and significant interaction between skills and IT consistent with complementarity between technology and human capital. The US*IT capital interaction remained significant[16]. Including fixed effects, however, rendered the skills variables and their interactions insignificant (even though US*IT interaction remains significant). Interactions between the US and skills were insignificant in all specifications. Another alternative is to assume that wages reflect marginal products of workers so that conditioning on the average wage in the firm is sufficient to control for human capital[17]. Interactions between the US dummy and average wages in the plant were also insignificant (p-value =0.512).

External Instruments

An alternative approach to identification uses external instruments based on changes to the tax treatment of IT and/or the differential roll out of Broadband across areas. We have data on broadband availability at the county level for 2003, and we plan to use it in the construction of our external instruments in the next months.

IVC Further Discussion of the Results

Cherry Picking?

One possibility raised by Criscuolo and Martin (2004) is that US firms "cherry pick" the best foreign establishments. To look at this issue we examined takeovers of plants by US firms relative to other sorts of takeovers in Table 7. Note first that the pre-takeover investment rates in IT for establishments taken over by US multinationals is actually slightly *lower* than that of other takeovers (not what might be expected from US firms cherry picking the high IT plants). For establishments taken over by US firms IT investment rates were equal to the four digit industry average for the whole sample, other multinationals were 7% above average and UK domestics were 5% above the average. These differences were not statistically significant.

[16] The linear educational term is negative in column (7) but it is positive at the mean (e.g. dropping the skills*IT interaction the marginal effect of education is 0.134).

[17] The problem is that wages may control for too much as some proportion of wages is almost certainly related to other factors apart from human capital. For example, in many models, firms with high productivity will reward

Column (1) of Table 7 examines IT investment for US takeovers; column (2) has non-US multinational takeovers and column (3) domestic takeovers. For all types of takeovers, IT investment rates fall during the takeover year relative to the year preceding the takeover. This is to be expected as there is likely to be restructuring during this period. For the US takeovers a different pattern emerges after the restructuring year – US firms significantly increased IT investment rates in the post-takeover year compared to the takeover period. This was not true for other firms whose IT investment rates post takeover did not change significantly from the takeover year[18]. Although sample sizes are small, this suggests that US firms genuinely change a domestic establishment's IT behavior following a takeover[19].

TFP Equations

To look at "excess returns" directly we also estimated TFP equations of the form of equation (6). These results are in Table 8. The first column is for IT intensive industries and the second for non-IT intensive industries. In column (1) the linear IT term (and the non-US multinational interaction) is statistically insignificantly different from zero. The key point is that the interaction between the US dummy and IT is significant and positive indicating that US firms apparently enjoy much greater returns on their IT investments than other equivalent firms. Column (2) shows that this is not true in the non-IT intensive sectors. This is consistent with the results from the simple production functions in the earlier tables.

The final four columns of Table 8 compare first differenced results to second, third and fourth differences. As with other work in this area the coefficients tend to rise as we move up to longer differences, but the change is very small (from 0.0105 in first differences to 0.0118 in fourth differences). Typically some of the increase in coefficients when moving from short to long differences is ascribed to attenuation bias. It may be that measuring IT carefully at the establishment (rather than firm or industry level) helps to alleviate some of these problems of measurement error.

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even homogenous workers with higher wages (see Nickell, Layard and Jackman, 1991 for examples of rent-sharing and efficiency wage models with this prediction and Van Reenen (1996) for some evidence).

[18] Testing the null that the post-takeover dummy for US firms is the same as for non-US MNEs is rejected (p-value =0.038). Similar results emerge if we use several years of post-takeover and pre-takeover information (p-value =0.078)

[19] Ideally we have liked to estimate a production function pre-takeover to examine whether the returns appeared to be higher for the plants who were taken over by a US firm relative to plants that were taken over by non-US firms. Unfortunately, this was not possible due to small sample size.

Software

Could the higher returns to IT be simply due to greater software intensity in US firms? We have some information of software expenditure that we can use to build analogous measures of the software IT stock. When included in the specifications these stocks are positive and significant, but the hardware coefficient is only slightly reduced. Compared to Table 3 column (2) when the software stock is included it has a coefficient of 0.0138 and a standard error of 0.0038. Conditional on this software stock the hardware coefficient is 0.0284 with a standard error of 0.0049. The hardware interaction with the US remains positive and significant when software is included. For example in column (7) of Table 4 the hardware interaction has a coefficient of 0.0366 with a standard error of 0.0169. One concern with comparing software data for multinationals versus domestic firms may be that some multinational software development happens in the home country, which is not fully measured through transfer pricing, so that multinational subsidiary software expenditure under-reports total software inputs. This emphasizes the importance, however, of comparing US multinationals to non-US multinationals that should have similar "underreporting" issues to the extent these occur. As noted above, whether or not we include these software measures, US multinationals still obtain a significantly higher return from IT inputs than either domestic firms or other non-US multinationals.

A possible explanation? Organization and management practices in US firms

We are still left with the puzzle of why IT returns appear to be higher for US firms. One possible explanation is that US firms are more organizationally devolved, enabling their workers to make more effective use of IT. New technologies increase the informational flows within firms, improving monitoring and allowing decision making to be pushed down within the firm. Firms with more devolved organisations should be able to exploit this and gain a higher return from IT. Bresnahan et al. (2002) present evidence for this phenomenon in a panel of US firms finding that organizational devolution and IT are significantly complementary.

To investigate whether greater organizational devolution could explain our findings of higher returns to IT for US multinational subsidiaries we exploit a new cross country data-set on organizational and management practices on around 750 firms in Europe and the US. This data set was collected in 2004 using an in-depth telephone survey on plant managers in medium sized manufacturing firms as part of a large LSE research project (see Bloom and Van Reenen (2005)). Table 9 presents new results from this data showing in column (1) that US firms (i.e. those incorporated in the US) are significantly more organizationally devolved than European firms, as defined by the Bresnahan et al. (2002) measures. In column (2) we look at firms in Europe and find that US-multinational subsidiary firms are also more devolved than either non-US multinational subsidiaries or domestic firms. While this data is not matched to our IT data and so is not a direct test of complementarities, it does show that US firms and their European multi-national subsidiaries are different, operating with flatter hierarchies with more control passed to lower level employees.

A linked explanation is that IT as a rapidly changing technology requires effective *management practices* (as well as organizational devolution) to be fully exploited. Because the capabilities of IT are constantly improving exploiting this will require ongoing change within the firm which well managed firms are much more likely to be able to cope with this uncertainty. This implies that better managed firms will be able to obtain higher returns from new IT technologies. Looking at the survey data in column (3) we see that US firms are indeed significantly better managed[20] than European firms, and in column (4) that US-subsidiaries in Europe are also significantly better managed than either non-US multinational subsidiaries or domestic firms. Again, this provides evidence of significant differences between US and European management practices, suggesting that the superior management practices of US multinational subsidiaries may explain their ability to extract higher returns from IT.

This is speculative, of course, but we are currently matching this management and organization data to IT information which will enable us to examine this hypothesis more directly.

[20] Management best practice is measured on the basis of an index that draws on 18 distinct questions across the areas of lean manufacturing, people management (such as merit-based promotion and incentive pay) and performance management. See Bloom and Van Reenen (2005) for details.

VI. CONCLUSIONS

Using a large and original establishment level panel dataset we find robust evidence that IT has a positive and significant correlation with productivity even after controlling for many factors such as fixed effects. We estimate that a doubling of the IT stock is associated with an increase in productivity of between 2% and 4%. Perhaps the most novel result is that we can account for the US multinational advantage in conventionally measured TFP by their higher returns to using IT capital. Furthermore, the stronger association of IT with productivity for US firms is confined to the same "IT using intensive" industries that largely accounted for the US productivity growth acceleration since the mid 1990s. US firms in the UK were able to get significantly more productivity out of their IT than other multinational (and domestic British) firms, even in the context of a UK environment. This suggests that part of the IT-related productivity gains in the US may be due to the management/organizational capital of firms rather than simply the "natural advantages" (geographical, institutional or otherwise) of the US environment.

A major research tasks remain in understanding *why* US firms are able to achieve these "IT friendly" organizational forms and their European counterparts cannot. It could be due to timing – US firms where closer to the development of the new wave of IT producers and so were the first to learn about them. In this scenario European firms will quickly catch up (although there is little evidence of this happening so far). A second explanation is that US firms are "leaner and meaner" than their European counterparts due to tougher competitive conditions in their domestic markets and are therefore intrinsically quicker to adapt to revolutionary new technologies. Alternatively, US firms may be more organizationally devolved for historical reasons due to their greater supply of college levels skills, relative absence of family owned firms and/or their history of technological leadership (see Acemoglu et al, 2005), rendering them better equipped to adopt new IT technologies. Under these scenarios Europe will resume the catching up process with a much longer lag that is conventionally thought.

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TABLE 1 - SUMMARY STATISTICS SAMPLE (2001 CROSS SECTION)

All Firms

Variable	Frequency	Mean	Median	Standard Deviation
Employment	7495	795.91	238.00	3943.87
Gross Output	7495	84,475.46	20,053.00	445,039.30
Value Added	7495	28,440.95	6,765.64	167,510.40
Capital per worker	7495	84.03	46.97	112.70
Value Added per worker	7495	38.92	28.26	52.69
Gross Output per worker	7495	118.89	81.08	132.32
Total Materials per worker	7495	79.37	44.47	102.60
IT Capital/ Gross Output	7495	0.0103	0.0041	0.02
IT expenditure per worker	7495	0.39	0.14	0.87
IT capital	7495	989.65	76.55	10,548.86
Materials as a share of gross output	7495	0.57	0.59	0.24
Labor costs as a share of gross output	7495	0.32	0.28	0.22
ln(IT Capital)	7495	4.44	4.34	2.02

Notes: All monetary amounts are in sterling in year 2000 prices, deflated using ONS four SIC digit producer price indexes; firm level value added is constructed as the sum of turnover, variation of total stocks, work of capital nature by own staff, insurance claims received minus purchases; total stocks are constructed as described in the Appendix. All variables in units of 1000s except ratios and employment.

TABLE 2 - DESCRIPTIVE STATISTICS BROKEN DOWN BY MULTINATIONAL STATUS

Panel A Summary Statistics (all in deviations from SIC4 year mean)

		Employment	Value added per Employee	Gross output per Employee	Capital per Employee	Materials per Employee	IT Capital per Employee
US Multinationals							
	Mean	151.19	123.23	121.48	124.74	123.36	141.23
	St. Deviation	248.12	124.96	106.37	123.89	118.18	189.93
	Observations	576	576	576	576	572	576
Other Multinationals							
	Mean	145.87	115.29	117.50	120.40	113.14	119.94
	St. Deviation	219.29	124.16	116.80	127.71	98.85	161.83
	Observations	2228	2228	2228	2228	2191	2228
UK domestic							
	Mean	72.39	90.05	89.23	87.48	91.12	85.71
	St. Deviation	120.92	100.05	100.94	122.36	123.26	178.14
	Observations	4770	4770	4770	4770	4747	4770

Notes: All variables expressed in deviations from the four digit industry mean in 2001. Firm level value added is constructed as the sum of turnover, variation of total stocks, work of capital nature by own staff, insurance claims received minus purchases; total and IT capital stocks are constructed using the perpetual inventory method as described in the text.

TABLE 3 – BASIC PRODUCTION FUNCTION ESTIMATES

Estimation Method	**(1) OLS, No FE**	**(2) OLS, FE**	**(3) OLS, FE**	**(4) GMM, Static**	**(5) GMM, Dynamic (Unrestricted)**	**(6) GMM COMFAC (Restricted)**	**(7) OLLEY-PAKES**
Dependent variable: ln(GO) = ln(Gross Output)							
Ln(C_t) IT capital	0.0440*** (0.0023)	0.0299*** (0.0040)	0.0265*** (0.0063)	0.0391*** (0.0171)	0.0656* (0.0373)	0.0430** (0.0211)	0.0204*** (0.0030)
Ln(C_{t-1}) IT capital, lagged	-	-	-	-	-0.0343 (0.0242)	-	-
Ln(M_t) Materials	0.5384*** (0.0080)	0.4665*** (0.0193)	0.4702*** (0.0283)	0.3998*** (0.0402)	0.3293*** (0.0750)	0.3595*** (0.0494)	0.5562*** (0.0102)
Ln(M_{t-1}) Materials, lagged	-	-	-	-	-0.0715 (0.0534)	-	-
Ln(K_t) Non-IT Capital	0.1193*** (0.0063)	0.1650*** (0.0153)	0.1953*** (0.0234)	0.1584*** (0.0410)	0.3618*** (0.0869)	0.2937*** (0.0526)	0.1511*** (0.0115)
Ln(K_{t-1}) Non-IT Capital, lagged	-	-		-	-0.1815*** (0.0592)	-	
Ln(L_t) Labour	0.2868*** (0.0062)	0.3177*** (0.0198)	0.2979*** (0.0209)	0.4158*** (0.0479)	0.2981*** (0.0829)	0.3524*** (0.0560)	0.2611*** (0.0080)
Ln(L_{t-1}) Labour, lagged	-	-		-	0.0091 (0.0624)	-	
Ln(Y_{t-1}) Gross Output, lagged	-	-	-	-	0.2330*** (0.0581)	-	-
Rho, ρ	-	-	-	-	-	0.3488*** (0.0291)	-
Observations	22,736	22,736	6,763	6,763	6,763	6,763	12,069
Fixed effects	**NO**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1st order serial correlation test	-	-	-	-3.634	-5.223	-	-
(p value)				*(0.000)*	*(0.000)*		
2nd order serial correlation test	-	-	-	-0.239	0.953	-	-
(p value)				*(0.811)*	*(0.341)*		
Sargan-Hansen Test	-	-	-	34.38	24.65	-	
(p value)				*(0.354)*	*(0.852)*		
COMFAC	-	-	-	-	-	6.7474	-
(p value)						*(0.1500)*	

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns is the log of gross output. The time period is 1995-2003. All variables are expressed in deviations from the 4 digit industry mean in the same year. The estimation method in columns (1) through (3) is OLS (with fixed efefcts in columns (2) and (3); .in columns (4) to (6) we use System-GMM (Blundell and Bond, 2000) and in column (7) we use Olley Pakes (1996). Standard errors in brackets under coefficients in all columns are clustered by establishment (i.e. robust to heteroskedacity and autocorrelation of unknown form). One step GMM results reported. All columns include age, foreign ownership and region dummies and a dummy taking value one if the firm belongs to a multi-firm enterprise group as additional controls. In columns (4) to (6) instruments are all plant level factor inputs lagged t-2 and before (when available) in the differenced equation (i.e. m_{t-2}, n_{t-2} ,k_{t-2},$c_{t-2,}$ q_{t-2}) and lagged differences in the levels equation (Δm_{t-1}, Δn_{t-1} , Δk_{t-1}, $\Delta c_{t-1,}$). Serial correlation tests are LM tests of the first differenced residuals (See Arellano and Bond, 1991). Sargan-Hansen Test of instrument validity is a test of the over-identification restrictions. Olley Pakes uses a fourth order series expansion to approximate the phi function. Standard errors in Olley-Pakes are block bootstrapped with 200 replications.

TABLE 4 – ALLOWING THE I.T. COEFFICIENT TO DIFFER BY OWNERSHIP STATUS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	**ln(GO)**	**ln(GO)**	**ln(GO)**	**ln(GO)**	**ln(GO)**	**ln(GO)**	**ln(GO)**	**ln(GO)**
Sectors	All Sectors	All Sectors	All Sectors	IT Using Intensive Sectors	Non IT Using Intensive Sectors	All Sectors	IT Using Intensive Sectors	Non IT Using Intensive Sectors
Fixed effects	**NO**	**NO**	**NO**	**NO**	**NO**	**YES**	**YES**	**YES**
Ln(C) **IT capital**	-	0.0434*** (0.0023)	0.0414*** (0.0025)	0.0357*** (0.0032)	0.0441*** (0.0034)	0.0293*** (0.0045)	0.0206*** (0.0066)	0.0271*** (0.0053)
USA*ln(C) **USA ownership*IT capital**	-	-	0.0108** (0.0047)	0.0191** (0.0075)	0.0066 (0.0060)	0.0084 (0.0093)	0.0295* (0.0155)	0.0009 (0.0108)
MNE*ln(C) **Non-US multinational *IT capital**	-	-	0.0037 (0.0028)	-0.0002 (0.0037)	0.0072* (0.0040)	-0.0016 (0.0050)	0.0046 (0.0081)	-0.0017 (0.0065)
Ln(M) **Materials**	0.5472*** (0.0081)	0.5383*** (0.0080)	0.5385*** (0.0080)	0.6138*** (0.0138)	0.5010*** (0.0100)	0.4662*** (0.0193)	0.5596*** (0.0275)	0.4115*** (0.0266)
Ln(K) **Non-IT Capital**	0.1295*** (0.0066)	0.1176*** (0.0063)	0.1178*** (0.0063)	0.1020*** (0.0082)	0.1344*** (0.0085)	0.1638*** (0.0153)	0.1396*** (0.0226)	0.2112*** (0.0224)
Ln(L) **Labour**	0.3152*** (0.0062)	0.2864*** (0.0062)	0.2858*** (0.0062)	0.2337*** (0.0098)	0.3031*** (0.0076)	0.3170*** (0.0197)	0.2537*** (0.0261)	0.3385*** (0.0247)
USA **USA Ownership**	0.0847*** (0.0109)	0.0745*** (0.0106)	0.0155 (0.0257)	-0.0566 (0.0394)	0.0510 (0.0339)	-0.0175 (0.0557)	-0.1671* (0.0925)	0.0157 (0.0646)
MNE **Non-US multinational**	0.0478*** (0.0067)	0.0414*** (0.0066)	0.0234 (0.0148)	0.0307 (0.0197)	0.0079 (0.0202)	0.0436 (0.0298)	-0.0090 (0.0516)	0.0451 (0.0363)
Observations	22,736	22,736	22,736	7,905	14,831	22,736	7,905	14,831
Adjusted R Squared	0.95	0.96	0.96	0.97	0.95	0.99	0.99	0.99

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns is the log of gross output. The time period is 1995-2003. All variables are expressed in deviations from the 4 digit SIC mean in the same year. The estimation method in all columns is OLS. . All columns include age, foreign ownership and region dummies and a dummy taking value one if the firm belongs to a multi-firm enterprise group as additional controls. Columns (6) to (8) include establishment level fixed effects. Standard errors in brackets under coefficients in all columns are clustered by firm (i.e. robust to heteroskedacity and autocorrelation of unknown form). See Appendix B for definition of IT using intensive sectors.

TABLE 5 – ALLOWING ALL PRODUCTION FUNCTION COEFFICIENTS TO VARY BY OWNERSHIP STATUS

Panel A: IT-Intensive Sectors

	(1)	(2)	(3)
Dependent variable	**ln(GO)**	**ln(GO)**	**ln(GO)**
Sample	**US firms**	**All firms except US firms**	**All Multinationals Except USA**
Fixed effects	**YES**	**YES**	**YES**
Ln(C)	0.0509***	0.0271***	0.0333***
IT capital	(0.0165)	(0.0044)	(0.0071)
Ln(M)	0.5696***	0.5463***	0.5189***
Materials	(0.0361)	(0.0181)	(0.0240)
Ln(K)	0.0901**	0.1321***	0.1161***
Non-IT Capital	(0.0407)	(0.0136)	(0.0205)
Ln(L)	0.2533***	0.2684***	0.2939***
Labour	(0.0481)	(0.0193)	(0.0258)
Establishments	416	3,829	1,373
Observations	767	7,138	2,600
Adjusted R Squared	0.91	0.94	0.95

F statistic of restrictions of coefficients across sub-samples (threshold at 1%=3.02, threshold at 5%=2.21, threshold at 10% level=1.84)

H_0: Coefficients on US firms the same as coefficients on non-US firms; F = 3.81

H_0: Coefficients on US firms the same as coefficients on other MNE's; F=3.27

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns is the log of gross output. The time period is 1995-2003. All variables are expressed in deviations from the 4 digit SIC mean in the same year. The estimation method in all columns is OLS. All columns include plant level fixed effects. Standard errors in brackets under coefficients in all columns are clustered by firm (i.e. robust to heteroskedacity and autocorrelation of unknown form). See Appendix B for definition of IT using intensive sectors.

TABLE 5 – ALLOWING ALL PRODUCTION FUNCTION COEFFICIENTS TO VARY BY OWNERSHIP STATUS, CONT.
Panel B: Non IT-Intensive Sectors

	(1)	(2)	(3)
Dependent variable	**ln(GO)**	**ln(GO)**	**ln(GO)**
Sample	**US firms**	**All firms except US firms**	**All Multinationals Except USA**
Ln(C)	0.0308***	0.0284***	0.0324***
IT capital	(0.0033)	(0.0050)	(0.0109)
Ln(M)	0.4294***	0.4479***	0.4586***
Materials	(0.0174)	(0.0311)	(0.0429)
Ln(K)	0.1907***	0.2011***	0.2025***
Non-IT Capital	(0.0144)	(0.0247)	(0.0538)
Ln(L)	0.3390***	0.3247***	0.3029***
Labour	(0.0169)	(0.0264)	(0.0706)
Establishments	7561	2599	537
Observations	14,831	5,393	1,025
Adjusted R Squared	0.90	0.91	0.91
Fixed effects	**YES**	**YES**	**YES**

F statistic of restrictions of coefficients across sub-samples (threshold at 1%=3.02, threshold at 5%=2.21, threshold at 10% level=1.84)

H_0: Coefficients on US firms the same as coefficients on non-US firms; F = 1.50

H_0: Coefficients on US firms the same as coefficients on other MNE's; F = 0.44

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns is the log of gross output. The time period is 1995-2003. All variables are expressed in deviations from the 4 digit SIC mean in the same year. The estimation method in all columns is OLS. All columns include plant level fixed effects. Standard errors in brackets under coefficients in all columns are clustered by firm (i.e. robust to heteroskedacity and autocorrelation of unknown form). See Appendix B for definition of IT using intensive sectors.

TABLE 6 – ROBUSTNESS TESTS ON PRODUCTION FUNCTIONS

Experiment	(1) Baseline Specification	(2) All Inputs Interacted	(3) Alternative functional form for IT	(4) Full "Translog" interactions	(5) Value Added	(6) US FDI in the 4 digit industry	(7) Skills
Dependent variable	ln(GO)	ln(GO)	ln(GO)	ln(GO)	ln(VA)	ln(GO)	ln(GO)
Ln(C) **IT capital**	0.0206*** (0.0066)	0.0188*** (0.0067)	-	0.0180*** (0.0061)	0.0498*** (0.014)	0.0165** (0.0068)	0.0242*** (0.0070)
USA*ln(C) **USA ownership*IT capital**	0.0295* (0.0155)	0.0434** (0.0220)	-	0.0286* (0.0150)	0.0670* (0.0363)	0.0259* (0.0156)	0.0165** (0.0082)
MNE*ln(C) **Non-US multinational *IT capital**	0.0046 (0.0081)	0.0050 (0.0097)	-	-0.0000 (0.0075)	-0.0087 (0.0195)	0.0029 (0.0084)	0.0037 (0.0075)
SKILLS*ln(C) **College %*IT capital**							0.0485** (0.0204)
Ln(M) **Materials**	0.5596*** (0.0275)	0.5582*** (0.0293)	0.5598*** (0.0270)	0.2532 (0.1922)	-	0.5603*** (0.0273)	0.6269*** (0.0126)
Ln(K) **Non-IT Capital**	0.1396*** (0.0226)	0.1459*** (0.0225)	-	0.2523*** (0.0904)	0.3119*** (0.0433)	0.1390*** (0.0224)	0.1042*** (0.0083)
Ln(Total_K) **Non IT capital + IT capital**	-	-	0.1687*** (0.0216)	-	-	-	
Ln(L) **Labour**	0.2537*** (0.0261)	0.2531*** (0.0284)	0.2511*** (0.0245)	0.4044** (0.1882)	0.5818*** (0.0462)	0.2558*** (0.0264)	0.2154*** (0.0098)
USA **USA Ownership**	-0.1671* (0.0925)	0.1096 (0.3409)	-0.0324 (0.0376)	-0.1595* (0.0870)	-0.3656* (0.2109)	-0.1479 (0.0931)	-0.0653 (0.0431)
MNE **Non-US multinational**	-0.0090 (0.0516)	0.0346 (0.2003)	0.0105 (0.0214)	0.0096 (0.0464)	0.0892 (0.1186)	-0.0002 (0.0526)	-0.0051 (0.0641)
USA*ln(M) **USA ownership*materials**	-	0.0034 (0.0475)	-	-	-	-	-

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MNE*ln(M) **Non-US multinational *materials**	-	0.0051 (0.0278)	-	-	-	-	-
USA*ln(K) **USA ownership*Non IT capital**	-	-0.0311 (0.0574)	-	-	-	-	-
MNE*ln(K) **Non-US multinational *Non IT capital**	-	-0.0144 (0.0201)	-	-	-	-	-
USA*ln(L) **USA ownership*Employment**	-	-0.0126 (0.0621)	-	-	-	-	-
MNE*ln(L) **Non-US multinational *Employment**	-	0.0075 (0.0316)	-	-	-	-	-
C/(Total Capital) **Fraction of IT Capital in Total Capital**	-	-	0.3280 (0.2010)	-	-	-	-
USA*[C/(Total Capital)] **USA ownership*Fraction of IT Capital in Total K**	-	-	0.9139*** (0.2928)	-	-	-	-
MNE*[C/(Total Capital)] **Non-US multinational *Fraction of IT Capital in Total Capital**	-	-	0.2479 (0.2978)	-	-	-	-
Skills **Proportion of people with a college degree in industry-region cell**	-	-	-	-	-	-	-0.2376* (0.1351)
US_SIC4*ln(C) **[% of US Multinationals in industry]*IT capital**	-	-	-	-	-	0.6863 (0.4960)	-
Observations	7905	7905	7905	7905	7905	7905	7751
Adjusted R Squared	0.99	0.99	0.99	1.00	0.95	0.99	0.97
Test on joint significance of all the interaction terms, excluding IT interactions (p-value)	-	*0.93*	-	-	-	-	-
Test on joint significance of all the US interaction terms, excluding IT (pvalue}	-	*0.76*	-	-	-	-	-
Test on all the other MNE's interaction terms, excluding IT (p-value)	-	*0.90*	-	-	-	-	-
Test on the other omitted “translog” terms (p-value)	-	-	-	*0.32*	-	-	-

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns is the log of gross output. The time period is 1995-2003. All variables are expressed in deviations from the 4 digit SIC mean in the same year. The estimation method in all columns is OLS. All columns except (7) include plant level fixed effects. Standard errors in brackets under coefficients in all columns are clustered by firm (i.e. robust to heteroskedacity and autocorrelation of unknown form). These results are for the IT intensive sectors only.

TABLE 7 – ESTIMATION OF IT INVESTMENT EQUATION ON TAKEOVER SAMPLE

	(1)	(2)	(3)
Dependent variable	I^C_t/C_{t-1}	I^C_t/C_{t-1}	I^C_t/C_{t-1}
Pre-Takeover	0.3434	0.1332	0.2242**
	(0.2228)	(0.1436)	(0.1016)
Post-Takeover	0.6171**	-0.1728	0.1050
	(0.2966)	(0.1608)	(0.1685)
Observations	83	324	1229
Sample	**US**	**MNE**	**UK**

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns (1), (2) and (3) is current IT investments divided by lagged IT capital. The time period is 1995-2003. All variables are expressed in deviations from the SIC4 mean of the relevant year. The sample is of establishments who were taken over in our sample period and we keep only the single year before the takeover, the year of the takeover and the year after the takeover. "US" indicates that the establishment was taken over by a US firm, "MNE" indicates the establishment was taken over by a non-US multinational and "UK" indicates that the takeover was by a UK firm. "Pre-takeover" is a dummy variable equal to unity if the period is the year before the takeover, "Post-takeover" is a dummy variable equal to unity if the period is the year after a takeover and the year of the takeover is the omitted base

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TABLE 8 – TFP BASED SPECIFICATIONS

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	**Δln(TFP)**	**Δln(TFP)**	**Δln(TFP)**	**Δln(TFP)**	**Δln(TFP)**	**Δln(TFP)**
Order of differencing	**First**	**First**	**First**	**Second**	**Third**	**Fourth**
Sectors	**IT Intensive Sectors**	**Non IT Intensive Sectors**	**All**	**All**	**All**	**All**
ΔLn(C)	0.0051	0.0075**	0.0105	0.0110	0.0115	0.0118
IT capital	(0.0033)	(0.0029)	(0.0022)	(0.0031)	(0.0063)	(0.0087)
Δ[USA*ln(C)]	0.0180**	-0.0031	-	-	-	-
USA ownership*IT	(0.0083)	(0.0071)				
Δ[MNE*ln(C)]	-0.0035	-0.0019	-	-	-	-
Non-US multinational *IT	(0.0048)	(0.0043)				
ΔUSA	-0.0101**	0.0222	-	-	-	-
USA Ownership	(0.0050)	(0.0450)				
ΔMNE	0.0389	0.0155	-	-	-	-
Non-US multinational	(0.03007)	(0.0259)				
Observations	3,454	6,797	10,251	4,128	927	406

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns is the change in "Four factor" Measured Total Factor Productivity (MTFP) where we have calculated MTFP as the change in log output less the growth of all four factor inputs (materials, labour, non-IT capital and IT capital) weighted by their shares in gross output. The dependent variable is in annualized differences (first differences in columns (1) through (3) and longer differences in columns (4) through (6) – e.g. column (4) is in second differences as indicated by "order of the differencing"). The time period is 1995-2003. All variables are expressed in deviations from the 4 digit SIC mean in the same year. The estimation method in all columns is OLS.

TABLE 9 - MANAGEMENT AND ORGANIZATIONAL PRACTICES OF US FIRMS AND US SUBSIDIARIES

	(1)	(2)	(3)	(3)
Dependent variable	**Organization**	**Organization**	**Management**	**Management**
US Firms	0.694***		0.217***	
	(0.217)		(0.073)	
European Firms (France, Germany or UK)	Baseline		Baseline	
US Multinational subsidiary		0.831*		0.466***
		(0.451)		(0.149)
Non-US Multinational subsidiary		-0.473		0.029
		(0.502)		(0.169)
European domestic firms		Baseline		Baseline
# of Firms	550	330	738	443
Firm Controls	Yes	Yes	Yes	Yes
Country Controls	No	Yes	No	Yes

Notes: Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Coefficients from OLS regressions with standard errors in parentheses (robust to arbitrary heteroskedasticity); single cross section. Columns (1) and (3) estimated on full sample, columns (2) and (4) estimated only on the European sample because the sample contains no subsidiary firms in the US. Baseline category in columns (1) and (3) is European firms (France, Germany or the UK). Baseline in columns (2) and (4) is domestic firms. "Organization" is the average Z-score for the 2 organizational questions taken from Breshnahan et al. (2002) covering "Task allocation" and "Pace setting" where a higher scores indicate greater worker autonomy (details in Bloom and Van Reenen (2005)). "Management" is the average Z-score for 18 questions on management practices where 1 is "*worst practice*" and 5 is "*best practice*" from Bloom and Van Reenen (2005). "Firm controls" includes controls for firm size and public/private status.

APPENDIX A: ECONOMETRIC MODELS

A.1 BASIC APPROACH

Re-consider the basic production function in equation (1) suppressing the tildes for simplicity

$$q_{it} = a_{it} + \alpha_{it}^{M} m_{it} + \alpha_{it}^{L} l_{it} + \alpha_{it}^{K} k_{it} + \alpha_{it}^{C} c_{it} \tag{A1}$$

We can exploit the fact that we have panel data on our plants and attempt to control for unobserved heterogeneity more rigorously. We attempt to deal with the endogeneity of the time varying inputs (IT capital, non-IT capital, labour and materials) through various panel data techniques for production functions (specifically System GMM and versions of Olley Pakes, 1996).

A.2 SYSTEM GMM

The basic equation we wish to estimate can be written in simplified form as

$$y_{it} = \theta x_{it} + u_{it} \tag{A2}$$

Where θ is the parameter of interest. Assume that the stochastic error term, u_{it}, takes the form

$$\begin{aligned} u_{it} &= \eta_i + \tau_t + \omega_{it} \\ \omega_{it} &= \rho \omega_{it-1} + \upsilon_{it} \end{aligned} \tag{A3}$$

The τ_t represent macro-economic shocks captured by a series of time dummies, η_i is an individual effect, and υ_{it} is a serially uncorrelated mean zero error term. The other element of the error term, ω_{it} is allowed to have an AR(1) component (with coefficient ρ) which could be due to measurement error or slowly evolving technological change. Substituting (A3) into (A2) gives us the dynamic equation

$$y_{it} = \pi_1 y_{it-1} + \pi_2 x_{it} + \pi_3 x_{it-1} + \eta^*{}_i + \tau^*{}_t + \upsilon_{it} \tag{A4}$$

The common factor restriction (COMFAC) is $\pi_1\pi_2 = -\pi_3$. Note that $\tau^*{}_t = \tau_t - \rho\tau_{t-1}$ and η_i*= (1-ρ)η_i.

In the main results section we present several econometric estimates of production functions (OLS, within groups and GMM). Blundell and Bond (2000) recommend a system GMM approach to estimate equation (A4) and impose the COMFAC restrictions by minimum distance. If we allow inputs to be endogenous we will require instrumental variables. In the absence of any obvious natural experiments we consider moment conditions that will enable us to construct a GMM estimator for equation (A4). A common method would be to take first differences of (A4) to sweep out the fixed effects:

$$\Delta y_{it} = \pi_1 \Delta y_{it-1} + \pi_2 \Delta x_{it} + \pi_3 \Delta x_{it-1} + \Delta\tau_t + \Delta\upsilon_{it} \tag{A5}$$

Since υ_{it} is serially uncorrelated the moment condition

$$E(x_{it-2}\Delta\upsilon_{it}) = 0 \tag{A6}$$

ensures that instruments dated t-2 and earlier[21] are valid and can be used to construct a GMM estimator for equation (4) in first differences (Arellano and Bond, 1991). A problem with this estimator is that variables with a high degree of persistence over time (such as capital) will have very low correlation between their first difference (Δx_{it}) and the lagged levels being used an instrument (e.g. x_{it-2}). This problem of weak instruments can lead to substantial bias in finite samples. Blundell and Bond (1998) point out that under a restriction on the initial conditions another set of moment conditions are available[22]:

$$E(\Delta x_{it-1}(\eta_i + \upsilon_{it})) = 0 \tag{A7}$$

This implies that lags of the first differences of the endogenous variables can be used to instrument the levels equation (A4) directly. The econometric strategy is then to combine the

[21] Additional instruments dated t-3, t-4, etc. become available as the panel progresses through time.

instruments implied by the moment conditions (A6) and (A7). We stack the equations in differences and levels (i.e. (A4) and (A5)). We can obtain consistent estimates of the coefficients and use these to recover the underlying structural parameters in (A2).

The estimation strategy assumes the absence of serial correlation in the levels error terms (υ_{it})[23]. We report serial correlation tests in addition to the Sargan-Hansen test of the over-identifying restrictions in all the GMM results[24].

This GMM "system" estimator has been found to perform well in Monte Carlo simulations and in the context of the estimation of production functions (Blundell and Bond, 2000). The procedure should also be a way of controlling for transitory measurement error (the fixed effects control for permanent measurement error).

A.3 OLLEY PAKES

Reconsider the basic production function[25]

$$q_{it} = \alpha^L l_{it} + \alpha^M m_{it} + \alpha^K k_{it} + \alpha^C c_{it} + \omega_{it} + \eta_{it} \tag{A8}$$

The "efficiency term", ω_{it}, is the unobserved productivity state that will be correlated with both output and the variable input decision and η_{it} is an i.i.d. error term (either measurement error or an unforecastable shock to productivity). We assume that both capital stocks are predetermined and current investment (which will react to productivity shocks) takes one period before it becomes productive, i.e. $I_{it}^K = I_{t-1}^K + (1-\delta^K)K_{it-1}$ and $I_{it}^C = I_{t-1}^C + (1-\delta^C)C_{it-1}$.

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[22] The conditions are that the initial change in productivity is uncorrelated with the fixed effect $E(\Delta y_{i2}\eta_i) = 0$ and that initial changes in the endogenous variables are also uncorrelated with the fixed effect $E(\Delta x_{i2}\eta_i) = 0$

[23] If the process is MA(1) instead of MA(0) then the moment conditions in (A6) and (A7) no longer hold. Nevertheless $E(x_{it-3}\Delta\upsilon_{it}) = 0$ and $E(\Delta x_{it-2}(\eta_i + \upsilon_{it})) = 0$ remain valid so earlier dated lags could still be used as instruments. This is the situation empirically with the wage equations.

[24] These are based on the first differenced residuals so we expect significant first order serial correlation but require zero second order serial correlation for the instruments to be valid. If there is significant second order correlation we need to drop the instruments back a further time period.

[25] For notational simplicity we abstract from plant age, but this we consider this in the implement this in the estimation routine along the same lines as Olley and Pakes (1996).

Extending the results in Pakes (1994) for two capital goods it can be shown that the investment policy functions for IT and non-IT are monotonic in non-IT capital, IT capital and the unobserved productivity state.

$$i_{it}^{K} = i^{K}(k_{it}, c_{it}, \omega_{it})$$

$$i_{it}^{C} = i^{C}(k_{it}, c_{it}, \omega_{it})$$

The investment policy rule can therefore be inverted to express ω_{it} as a function of investment and capital. We choose to focus on the non-IT investment policy function which is inverted to obtain the proxy:

$$\omega_t^{K}(i_{it}^{K}, k_{it}, c_{it})$$

The first stage of the OP algorithm uses this invertibility result to re-express the production function as:

$$y_{it} = \alpha^{L} l_{it} + \alpha^{M} m_{it} + \alpha^{K} k_{it} + \alpha^{C} c_{it} + \omega_t^{K}(i_{it}^{K}, k_{it}, c_{it}) + \eta_{it} = \alpha^{L} l_{it} + \alpha^{M} m_{it} + \phi(i_{it}^{K}, k_{it}, c_{it}) + \eta_{it}$$

where $\phi(i_{it}^{K}, k_{it}, c_{it}) = \phi_t = \omega_t^{K}(i_{it}^{K}, k_{it}, c_{it}) + \alpha^{K} k_{it} + \alpha^{K} c_{it}$

We approximate this function with a series estimator that previous applications have shown to be close to the fully non-parametric approximation. We can use this first stage results to get estimates of the coefficients on the variable inputs. The second stage of the OP algorithm is

$$y_{it}* = y_{it} - \alpha^{L} l_{it} - \alpha^{M} m_{it} = \alpha^{K} k_{it} + \alpha^{C} c_{it} + \omega_{it} + \eta_{it}$$

Note that the expectation of productivity conditional on last period's information set (denoted Ω_{t-1}) is

$$\omega_{it} |_{\chi_{it}=1} = E[\omega_{it} \mid \omega_{it-1}, \chi_{it} = 1] + \xi_{it}$$

where $\chi_{it} = 1$ indicates that the firm has chosen not to shut down (in the empirical results we experiment with also allowing for a selection stage over the decision to exit). This expression for the productivity state follows from the assumption that unobserved productivity evolves as a first order Markov process. Again we assume that we can approximate this relationship with a high order series approximation g(ω_{it-1}).

Substituting this in to the "second stage" and taking expectations conditional on last period's information set gives us

$$E(y_{it}*|\Omega_{t-1}) = \alpha^K k_{it} + \alpha^C c_{it} + g[\phi(i^K_{it-1}, k_{it-1}, \alpha^C c_{it-1}) - \alpha^K k_{it-1} - \alpha^C c_{it-1}]$$

Since we already have in hand estimates of the ϕ_{t-1} function this amounts to estimating by Non-Linear Least Squares (NLLS). This now gives us all the relevant parameters of the production function.

There are numerous extensions to the basic Olley-Pakes methodology that have been suggested. First, we consider the additional selection correction originally suggested by the authors[26]. Second, Levinsohn and Petrin (2003) suggest using intermediate inputs as an alternative proxy for the unobserved productivity term. This has attractions in plant level data where investment is zero in a non-trivial number of cases.

Ackerberg, Caves and Frazer (2005) and Bond and Soderbom (2005) emphasis the identification problems underlying the original OP set up which implicitly requires variation in firm specific input prices. The latter argue for the GMM approach discussed in the previous sub-section which is identified in the presence of differential adjustment costs. Katayama et al (2003) propose an approach that takes imperfect competition more seriously and allows for differential firm specific mark-ups and implement a nested logit approach. Unfortunately their approach requires constant marginal costs and instant adjustment of the capital stock – rather unpalatable assumptions in our context.

[26] This made little difference to the results so the tables report teh non-se ;ectivity corrected results.

APPENDIX B: DATA APPENDIX

B1 ESTABLISHMENT DATASET ABI

The Annual Business Inquiry (ABI) is the major source of establishment level data in the UK[27]. It underlies the construction of aggregate output and investment in the national accounts and is conducted by the Office of National Statistics (ONS). The ABI is a stratified random sample: sampling probabilities are higher for large establishments (e.g. 100% for all establishments with more than 250 employees). Each establishment has a unique "reporting unit reference number" (RUREF) which does not change when a plant is taken over by a new firm, for example. Data on the production sector (including manufacturing) is in the ABI which has a long time series element (from 1980 and before in some cases). Data on the non-production sector (services) is available for a much shorter time period (from 1997 onwards). The sample is large: in 1998 alone there are 28,765 plants in the production sector alone (Haskel and Martin, 2002).

The questionnaire sent out on the ABI is extensive and covers all the variables needed to estimate basic production functions. In particular we have gross output, value added, employment, wage bill, investment and total materials (this includes all intermediate inputs – energy, materials, etc.).

B2 Information Technology Datasets

Working closely with statisticians and data collectors at ONS we combined the four major IT surveys and matched this into the ABI establishment data using the common establishment code (the Inter-Departmental Business Register, or IDBR). The three IT hardware surveys were not designed to cover exactly the same establishments as contained in the ABI survey, but because there is over-sampling of the larger establishments in all surveys the overlap is substantial, especially for the larger plants.

The main IT surveys include the Business Survey into Capitalized Items (BSCI), the Quarterly Inquiry into Capital Expenditure (QICE) and the Fixed Asset Register (FAR). The

[27] For a more detailed description see Barnes and Martin (2002).

ABI also has additional questions on software included since 2000. These surveys are compiled at the reporting unit level, and contain information on the value (in thousands of pounds) of software and hardware acquisitions and disposals. Once the stocks are built within each different survey, we combine them across surveys and, for hardware and software separately, we build across-surveys stocks[28]. We have some concerns about the accuracy of the plant reports of software expenditure (we are currently investigating these), so we focus in the main part of the paper on the IT hardware stocks.

In the following paragraphs we first describe the different surveys; we then illustrate the details of the PIM used for the construction of the stocks and the procedure followed to build across-surveys variables.

Data Sources

Business Survey into Capitalized Items (*BSCI).* The BSCI asks for detail of acquisitions and disposals of capital in more than 100 categories, including computer hardware and software. The survey is annual and runs between 1998 and 2003; we dropped the 1998 cross section due to concerns over reliability expressed by the data collectors. There is 100% sampling frame for the largest 750 businesses and a stratified random sample of medium sized businesses (between 100 and 750 workers). The BSCI contributes about 1,500 to 2,000 observations for each year between 1999 and 2002.

Quarterly Inquiry into Capital Expenditure (QICE). The QICE provides information of hardware and software investments from 2000Q1 until 2003Q4. The inquiry selects 32,000 establishments each quarter. Of these 32,000 companies, all establishments with over 300 employees are selected each quarter. Businesses with fewer employees are selected for the inquiry randomly. Each quarter one fifth of the random sample is rotated out of the sample and a new fifth is rotated in. The quarterly data have been annualized in several alternative ways and we checked the robustness of the results across these. First, we extrapolated within year for establishments with missing quarters[29]. As a second alternative, we constructed an

[28] We are careful to check for differences in coefficients due to the IT measures coming from different surveys. We could not reject the assumption that there were no significant different differences in the IT coefficients arising from the fact that the IT stocks were built from different surveys.

[29] The extrapolation was done by simple averaging, but we also tried more sophisticated quarterly models taking into account the quarter surveyed. This made practically no difference.

indicator that gives the number of non-missing values that exist for each year and establishment and included this as an additional control in the regressions. Third, we dropped observations constructed from less than four full quarters. The results were quite robust across all three methods and the Tables report results based on the first method.

Fixed Asset Register (FAR). The FAR asks for the historic cost (gross book value) of the fixed asses held on the firms' asset register, broken down by the years of acquisition. The survey provides information on IT hardware assets only, and covers the years 1995 up to 2000. The survey provides information for about 1,000 hardware observations.

Annual Business Inquiry (ABI). The ABI contains a question on software expenditures from 2000 onwards. There are approximately 20,000 non-zero returned values for software investments in each year.

Estimation of IT capital stocks

We build stocks of IT capital applying the Perpetual Inventory Method (PIM) to the IT investment data (and the non-IT investment data) described above. The basic PIM equation is:

$$K_{it}^{h} = I_{it}^{h} + \left(1-\delta^{h}\right)K_{it-1}^{h} \quad \text{(B1)}$$

where I_t^h represents real investment of asset type *h* (e.g. computer hardware, I_t^C) and δ_t^h is the asset specific depreciation rate. To construct real investment we deflate nominal investments using the economy-wide (asset specific) hedonic price indices for software and hardware provided by the NIESR (which are based on Jorgensen's US price deflators). We rebased to the year 2000 for consistency with the other PPI deflators (see below).

Estimation of TFP and capital services

To calculate the user cost (e.g. ρ^C is the rental price of IT capital) we use the Hall-Jorgensen formulation:

$$\rho_t^h = \frac{1-A^h{}_t}{1-T_t^h}[r_t + \delta_t^h - ((p_t^h - p_{t-1}^h)/p_{t-1}^h)]p_t^h \quad \text{(B2)}$$

where ρ^h is the rental price of asset class h, r is the nominal interest rate, δ is the depreciation rate of the asset, and p^h is the asset price. The tax parameters are given by A which is the present-discounted value of depreciation allowances, and T which is the rate of corporate profits tax. We obtained user costs from the data underlying Oulton and Srinivasan (2004) kindly provided by the authors. These are economy wide

We can then calculate total profits as[30]

$$\Pi_{it} = \sum_h \rho_t^h K^h{}_{it} \tag{B3}$$

The share of each asset class in revenue is then

$$s_{it}^h = \frac{\rho_t^h K^h{}_{it}}{\sum_h \rho_t^h K^h{}_{it}} \frac{\sum_h \rho_t^h K^h{}_{it}}{pY} = \frac{\rho_t^h K^h{}_{it}}{\Pi_{it}} \frac{\Pi_{it}}{p_t Y_{it}} \tag{B4}$$

that is used in calculating measured TFP in equation (7) and elsewhere.

Zeros

Both the BSCI and the QICE code missing values as zeros. While in the BSCI we are able to identify actual zero investments through a specific coding, for the QICE this is not possible. In the construction of the capital stocks we treated the zero investments observations as actual absence of IT investments. In the regressions we drop observations with zero IT capital stocks

Interpolations

In order to maximize the number of observations over which we could apply the PIM, we interpolated net investment observations for a single year of data if we observed investment the year before and the year afterwards. This affected only 2.8% of the observations in the regression sample and results are robust to dropping these observations.

[30] Note that empirically there are alternative ways to approach equation (B3). Our preferred method is to calculate $s_{it}^h = \frac{\rho_t^h K^h{}_{it}}{\Pi_{it}} \frac{\hat{\Pi}_{it}}{p_t Q_{it}}$ where Π_{it} is taken from equation (B3) and $\hat{\Pi}_{it}$ is taken as the residual of revenues less materials and the wage bill.

Initial Conditions

In order to apply the PIM methodology, we need to approximate a starting value to start the recursion. We apply a similar methodology as the one devised by Martin (2005) to construct establishment level capital stocks in the ARD. For each firm, we first build two digit industry-specific IT Investment/Capital ratios using the NISEC02 industry level data-set provided by the NIESR, which contains separate time-series data on hardware and software capital stocks and runs up to 2001 (these are based on the input-output tables starting in 1975). We then use the ratio of the establishment's IT investment flow to the industry investment flow (denoted w_{it}^{A} for method "A") to impute the IT capital stock (i.e. we are assuming that the establishment's share of the IT capital stock in the industry is equal to the establishment's share of IT investment in the industry in the initial year). More precisely, we assume that for $t = 0$ only the initial plant level IT capital stock C_{i0}^{A} is:

$$C_{i0}^{A} = \mathrm{w}_{\mathrm{it}}^{\mathrm{A}}\, \mathrm{C}_{jt} \;\forall\; i \in j\,; \mathrm{w}_{\mathrm{it}}^{\mathrm{A}} = \left(\frac{I_{it}^{C}}{I_{jt}^{C}} \right)$$

where j represents an industry so a j sub-script represents an industry total – i.e. I_{jt}^{C} is total industry IT investment and C_{jt} is the total IT capital stock in time t. We apply this approximation to determine our initial condition in the first year that the establishment appears in our sample. For greenfield sites this is not an issue as their capital stock is zero. After the first year, we simply apply the PIM method.

Some of the establishments that we observe only for the first time may be investing systematically at a different rate from the industry average. To check weather our results were driven by the methodology used to build the initial conditions, we considered an alternative methodology based on employment weights (method "B"). For the first time we observed a plant in our sample we assumed that:

$$C_{i0}^{B} = w_{it-1}^{B} C_{jt-1}(1-\delta) + I_{it}^{C}$$

$$w_{it-1}^{B} = \frac{L_{it-1}}{L_{j-1}} \qquad \forall\, i \in j$$

So this is assuming that the establishment's share of the industry IT stock in the initial period is equal to the establishment's share of employment.

Depreciation

For all IT capital (software and hardware) we chose a depreciation rate of 36%. This choice is consistent with the analysis by methodology followed by the BEA which, in turn, derives from the study by Doms, Dunn, Oliner and Sichel (2004). In this study, the depreciation rate for PC's is estimated at approximately 50%, this value including both obsolescence and reevaluation effects. Since – as the BEA - we use real IT investments we have to use a lower depreciation rate to avoid double counting of the revaluation effect, included in the price deflators.

Basu et al (2003) argue that the true geometric rate of depreciation should be, in fact, approximately 30%. The significance and the magnitude of the coefficient obtained for both hardware and software are not affected by the exact choice of the alternative depreciation rate. We also experimented with the extreme assumption of 100% depreciation rate for IT, thus working directly with the flows. Results are in Appendix Table 2 which shows a significant coefficient with a lower point estimate than in the main table.

Across-Survey Stocks

Following the steps described above, we obtain hardware and software stocks within each different survey. We then matched our IT dataset with the ABI sample with non missing observations on other inputs and outputs (value added and gross output). In order to simplify the empirical analysis, we combined all the information of the different the surveys constructing overall across-surveys IT stocks for both hardware and software. Our strategy is to use the BSCI measure as the most reliable observation (as recommended by the data collectors). We then build our synthetic measure using the QICE stocks if the BSCI observation is missing or equal to zero and the QICE is different from zero. We finally use the FAR if both QICE and BSCI are missing and/or equal to zero and the FAR is not. For the software capital stock we also use the ABI information, following the same order described above. The sources of the aggregate capital stocks are summarized in the following table:

Source	Hardware Capital	Software Capital
BSCI	3,704	2,387
QICE	17,517	13,049
FAR	686	881
ABI	-	43,735

In order to keep track of the possible measurement error introduced using this procedure, we introduce in all the IT regressions a dummy that identifies the provenience of the observation for both the hardware and the software stocks. These dummies and their interactions with the IT coefficients are not significantly different from zero.

A small portion of the firms included in our dataset responded to more than one survey. We use some of this overlapping sample to get a better understanding of the measurement error in the data. By comparing the reports from the same establishments we calculate that there is much more measurement error for software than for hardware, which is why we currently focus on hardware. We did not find any evidence that the measurement error for hardware was greater for US firms than other firms, however, which is reassuring.

B3 OTHER DATA

PPI deflators

We deflate gross output using the PPI deflators 2000 based provided by the ONS. For the manufacturing sector, the deflators are usually available at the 4 SIC digits level (MM17 PPI deflators). Whenever this was not the case, we used a general deflator for the 2 digit industry or a deflator relative to the overall manufacturing sector. For the service sector we used a set of experimental deflators generated by the ONS. These deflators refer to a limited number of 5 SIC digits industries. For all the other industries we use the general deflator for the overall service sector.

Skills

In our analysis we use industry and/or region and/or year specific skills measures built using the Labour Force Survey data set. Our preferred measure of skills is the proportion of people in the sample having as a highest qualification a degree or equivalent and/or a title defined as “higher education” by the standard LFS classifications (post GSE A levels), even though the results are not qualitatively different once we use only the proportion of people with a degree.

We use LFS data from 1993 to 2003. First, we keep only observations referring to people between 24 and 64 years. We drop observations for which no information is available on education. The cells over which the proportion is computed are defined by two digit industry, one digit region and year (we also considered four and three digit industry and area-only definitions). For each index, we drop observations that are based on less than 50 observations. We use the number of observations of the LFS cells as weights for the skills regressions. We also constructed similar datasets, containing information on education as well as wages and hours worked. These indexes are built only for observations having non-missing values for these additional variables.

B4 CLEANING

We used standard procedures to clean the ABI and the IT data. First, we dropped all observations with negative value added and/or capital stock. Secondly we dropped the top and bottom percentile of the distribution of $\frac{\Delta X}{X}$ for employment and gross value added. Thirdly, we dropped extreme values of total capital stock per employee and gross value added per employee. This step of the cleaning procedure was performed on the overall ARD sample.

We applied a similar cleaning procedure also to our across surveys IT variables. For hardware IT variables (investments and capital stocks) we dropped the top and bottom percentiles of the ratio of the variables on gross value added[31].

B5 DEFINITION OF IT INTENSIVE USING INDUSTRIES

We focus on “IT intensive” sectors that are defined to be those that use IT intensively according to (Van Ark et al, 2002) who base their definitions on Stiroh (2002). The basic splits between industries that are intensive in “IT use” are based on the proportion of IT capital services in total capital services. This uses US data to calculate the service flows as these are more accurate than service flow calculations based on UK data. The industries are split based on the median proportion of IT capital service flows in total capital service flows.

The following sectors are IT intensive. Note that the other “non-IT intensive” sectors include the sectors that produce IT intensively. We also considered these as a separate category but found in relation to their IT coefficients they were significantly different from the sectors that used IT intensively. All industries are based on ISIC Revision 3.

[31] The results of the regression are qualitatively similar if the ICT data are cleaned using the ratio investments or stocks per employee.

APPENDIX TABLE 1: BREAKDOWN OF INDUSTRIES

IT Intensive (Using Sectors)

IT-using manufacturing

18 Wearing apparel, dressing and dying of fur
22 Printing and publishing
29 Machinery and equipment
31, excl. 313 Electrical machinery and apparatus, excluding insulated wire
33, excl. 331 Precision and optical instruments, excluding IT instruments
351 Building and repairing of ships and boats
353 Aircraft and spacecraft
352+359 Railroad equipment and transport equipment
36-37 miscellaneous manufacturing and recycling

IT-using services

51 Wholesale trades
52 Retail trade
65 Financial intermediation
66 Insurance and pension funding
67 Activities related to financial intermediation
71 Renting of machinery and equipment
73 Research and development
741-743 Professional business services

Non- IT Intensive (Using Sectors)

Non-IT intensive manufacturing

15-16 Food drink and tobacco
17 Textiles
19 Leather and footwear
20 wood
21pulp and paper
23 mineral oil refining, coke and nuclear
24 chemicals
25 rubber and plastics
26 non-metallic mineral products
27 basic metals
28 fabricated metal products
34 motor vehicles

Non-IT Services

50 sale, maintenance and repair of motor vehicles
55 hotels and catering
60 Inland transport
61 Water transport
62 Air transport

63 Supporting transport services, travel agencies
70 Real estate
749 Other business activities n.e.c.
75 Public Admin and welfare
80 Education
85 Health and Social Work
90-93 Other community, social and personal services
95 Private Household
99 Extra-territorial organisations

Non-IT intensive other sectors
01 Agriculture
02 Forestry
05 Fishing
10-14 Mining and quarrying
50-41 Utilities
45 Construction

IT Producing manufacturing
30 Office Machinery
313 Insulated wire
321 Electronic valves and tubes
322 Telecom equipment
323 radio and TV receivers
331 scientific instruments

IT producing services
64 Communications
72 Computer services and related activity

APPENDIX TABLE 2 - ALTERNATIVE ASSUMPTIONS ON I.T. CAPITAL STOCK CALCULATIONS

	(1)	(2)	(3)
Dependent variable	**ln(GO)**	**ln(GO)**	**ln(GO)**
Ln(M)	0.4640***	0.4657***	0.4662***
Materials	(0.0215)	(0.0213)	(0.0215)
Ln(K)	0.1669***	0.1516***	0.1755***
Non-IT Capital	(0.0181)	(0.0170)	(0.0185)
Ln(L)	0.3183***	0.3116***	0.3277***
Labour	(0.0243)	(0.0238)	(0.0245)
Ln(C)	0.0301***	0.0595***	-
hardware capital	(0.0045)	(0.0082)	
Ln (I^C)	-	-	0.0115***
IT Investment flow			(0.0025)
Firms	10648	10648	10648
Observations	19587	19587	19587
Adjusted R Squared	0.99	0.99	0.99
IT Measure	Standard	Employment Weights	Investments
Sample	All Sectors	All Sectors	All Sectors
Fixed effects	**YES**	**YES**	**YES**

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in all columns is the log of gross output. The time period is 1995-2003. All variables are expressed in deviations from the 4 digit SIC mean in the same year. The estimation method in all columns is OLS. All columns include plant level fixed effects. Standard errors in brackets under coefficients in all columns are clustered by firm. Column (1) uses the preferred IT measure (investment weights), Column (2) uses the alternative IT measure (employment weights), Column (3) uses hardware investment flow.