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Information Technology, Organisational Change and Productivity Growth: Evidence from UK Firms

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Abstract

We examine the relationships between productivity growth, IT investment and organisational change (ΔO) using UK firm data. Consistent with the small number of other micro studies we find (a) IT appears to have high returns in a growth accounting sense when ΔO is omitted; when ΔO is included the IT returns are greatly reduced, (b) IT and ΔO interact in their effect on productivity growth, (c) non-IT investment and ΔO do not interact in their effect on productivity growth. Some new findings are (a) Δ*O* is affected by competition; (b) US-owned firms are much more likely to introduce ΔO relative to foreign owned firms who are more likely still relative to UK firms; (c) our predicted measured TFP growth slowdown for firms who are not doing Δ*O* and/or are in the early stages of IT investment compare well with the macro numbers documenting a UK measured TFP growth slowdown.

Keywords: information technology, productivity growth, organisational change
JEL Classifications: D24, E22, L22, 031

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1 Introduction

With the extraordinary pervasiveness of information technology (IT) in modern economies, understanding the impact of IT on productivity growth is a matter of major importance for academics, business and policymakers. Two particular questions have arisen in the literature. First, how does IT interact with other factors of production to influence productivity? Second, and perhaps related, why have many European countries, who have been building up a share of IT capital comparable to the US, had slowdowns in total factor productivity growth?

One suggested answer to this puzzle is that (a) computer investment requires complementary investment in organisational capital, O (and thus organisational change ΔO) to obtain productivity gains and (b) such investment in O requires diverting resources away from current production. Thus (a) if firms or nations do not undertake such investment, they fail to get the productivity gains, and/or (b) whilst they are undertaking such investment their measured productivity growth might slow down (as they devote employment to this investment and away from current production).[1]

There are (at least) two issues surrounding this literature. First, as for the evidence base, the evidence from macro data is rather mixed (Basu et al, 2003), but without a ready macro measure of organisational change it is still rather a matter of conjecture. There is relatively little micro evidence, mostly because it is very hard to find systematic micro data on all of output, IT, other inputs and organisational measures.[2] Examples of such papers are Bresnahan, Brynjolfsson and Hitt (2002, BBH), papers by Ichniowski and Shaw and co-authors (summarised in Ichniowski and Shaw, 2003), and Black and Lynch (2003) but this literature is still small and mostly confined to the US.[3] A second issue is that, as is well acknowledged, ΔO is likely endogenous. Thus an account of the impact of ΔO would be more complete if there were an explanation of what drives ΔO in firms.[4]

This paper uses UK firm-level panel data on productivity, IT and organisational change to try to shed light on both these issues. Some of our findings we believe to be of interest since they are consistent with findings in data for the US. But some of our findings we believe add to the extant literature.

We have four findings that are consistent with other studies. First, IT appears to have high returns in a growth accounting sense when one omits ΔO, which then fall when ΔO is included. Second, IT and ΔO interact in their effect on productivity growth. Third, there is no additional impact on productivity growth from the interaction of ΔO and *non*-IT investment. Fourth, above-average periods of investment in IT are

[1] An alternative explanation is that the poor EU productivity growth results in large part from relatively poor productivity growth in wholesaling and retailing. This might in turn be due in part to planning regulations, but since wholesaling and retailing uses IT intensively it could also be due to relatively "poor" use of the IT capital stock. Note too that economies trying to catch up to US IT levels will be investing heavily in IT capital the adjustment costs of which might depress measured TFP growth.

[2] As Black and Lynch (2001) point out, there are case studies of IT and organisational change. There are also many articles on IT and wage inequality which is not our central concern here, see e.g. Bresnahan (1999).

[3] Caroli and van Reenen (2001) look at the effect of organisational change and its determinants, but their main focus is on skills (they have some evidence on organisational change and productivity in France, see below).

[4] BBH emphasise their primary concern is not endogeneity of O, but to document the co-movement of O and IT; while Ichniowski and Shaw (2003) for example emphasise endogeneity.

associated with slowdowns in measured TFP in the short run. These first three findings are all consistent with the suggestion from the macro data and the evidence from the micro data that IT and ΔO together boost productivity growth (Brynjolfsson and Hitt, 2003, and BBH) and the fourth finding uses micro data to confirm the macro suggestion that bursts of (IT) investment slow down measured TFP growth .

We have in addition, three broad findings that, we believe, add to the extant literature. The first two speak to the question of what determines ΔO. First, we find that ΔO is affected by competition. When we measure competition by lagged changes in market share we find that firms who lose market share in previous periods are statistically significantly more likely to introduce ΔO in the current period. Second, we also find strong effects on the probability of introducing ΔO from ownership. US-owned firms are much more likely to introduce ΔO relative to other non-UK firms who are more likely still relative to UK firms. These findings help interpret, we believe, results in Bloom, Sadun and van Reenen (2006) who find that US MNEs operating in the UK have higher returns to IT than non-US MNEs operating in the UK. They speculate that this is due to improved O in US MNE but have no data on O. Our results, which include data on ΔO, support this explanation. Our third finding relates to the macro literature. Our micro estimates imply a slowdown in measured TFP growth for firms with growing investment in IT and not undertaking ΔO (these might be for example UK firms in the early stages of IT adoption). This predicted slowdown is in line with observed UK TFP growth slowdown in the macro data.[5]

As in all empirical studies our findings should be treated with caution due, as we discuss, to measurement problems and our short panel. But our findings are suggestive of a story that might account for the IT/productivity growth puzzle set out above. It is that (a) successful productivity growth needs both IT and organisational change; (b) periods of above average investment lower measured TFP growth; (c) competition pressures firms to introduce organisational change and (d) US firms, controlling for competition, implement organisational change more readily than other firms. Quite why they do so is not something that we can answer with our data. Nonetheless we regard the finding of interest and suggestive of areas for future fruitful work.

The rest of the paper proceeds as follows. In section 2 we set out a framework to understand the key questions involved in our and other approaches. Section 3 describes the data, section 4 our results for productivity, section 5 results for organisational change, section 6 instrumental variables and wider implications. Section 7 summarises and concludes.

[5] We also believe that this paper contributes to work on the Community Innovation Survey. As well as working on production functions and IT, that we do not believe has been explored before, we have undertaken a good deal of robustness checking of the CIS (comparing with administrative data, text analyses of CIS responses) which we believe also contributes to understanding the accuracy of this survey. See below and the Data Appendix for details.

2 Overall approach

2.1 Simplified model

We start with a very simple model set out purely to motivate our approach and understand its relation with other work. Consider a production function of the form

$$Y_{it} = Y(F(K_{it}^{IT}, O_{it}), X_{it}, L_{it}^{P}) \tag{1}$$

where i, t denotes firm i in period t, Y is real output, K^{IT} is IT capital stock, O is organisational capital, L^{P} denotes workers used in production (explained below) and X are all other factors some of which might be observed such as non-IT capital stock K^{NIT}, and some are unobserved. Two assumptions are usually made about (1). First, it is usually argued that O and K^{IT} might be complementary in production and so to capture this we write these two factors within *F()*.[6] Second, it is often assumed that not all L workers are immediately productive; rather L^{P} workers are engaged in immediate production, with the remaining L^{O} workers are engaged in activities that are not immediately productive (e.g. formal or informal time spent on developing new processes) all of which might contribute to future O. Thus

$$L_{it}^{P} = L_{it} - L_{it}^{O} = L_{it}(1-(L_{it}^{O}/L_{it})) \tag{2}$$

Log linearising (1) and using the approximation from (2) that $logL^{P}=logL-(L^{O}/L)$ gives

$$y_{it} = \alpha_0 + \alpha_1 x_{it} + \alpha_2 l_{it} - \alpha_2 \left(L_{it}^{0}/L_{it}\right) + \alpha_3 k_{it}^{IT} + \alpha_4 O_{it} + \alpha_5 (k_{it}^{IT} * O_{it}) \tag{3}$$

where lower case letters denote logs (and O is upper case since it is a dummy in our data). Equation (3) is a standard production function, with the exception of the k^{IT} and O interaction and the term in (L^{O}/L). A first differenced version[7] of (3) can be written

$$\Delta y_{it} = \alpha_1 \Delta x_{it} + \alpha_2 \Delta l_{it} - \alpha_2 \Delta\left(L_{it}^{0}/L_{it}\right) + \alpha_3 \Delta k_{it}^{IT} + \alpha_4 \Delta O_{it} + \alpha_5 (\Delta k_{it}^{IT} * \Delta O_{it}) \tag{4}$$

Equations (3) and (4) highlight some questions of interest in the literature. First, there are a series of questions concerning O and k^{IT}: do they interact, does the omission of O overstate the returns to k^{IT}, does O or ΔO interact with other variables (e.g. skills, k^{NIT})? Second, if investing in IT requires co-investment in O

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[6]The use of interactions to address complementarities follows BBH (p.354). By including only K^{IT} as an interaction with O, we are implicity assuming that we do not expect any effect from O on non IT capital. Athey and Stern (1998) present a formal model whereby where organisational design is composed of a number of work practices. Complementarity arises, intuitively in the two factor case, where the returns to adopting practice 1 are higher when practice 2 has been adopted, see their equation (4). Our ΔO measure is a dummy, see below, so we are unable to precisely estimate underlying continuous functional forms. We model this complementarity by allowing firms who do organisational change to have higher returns to their investment in IT.

which takes L away from current production, then (L^O/L) rises in periods of IT investment, which, from (4), potentially leads to measured TFP growth falling in periods of IT investment; is this a big effect? Third, what determines O (and indeed the other variables)?

Equations (3) and (4) also highlight some of the problems in answering these questions. First, data on all these variables is rarely found. Many company level data sets might have data on Y and K but few also subdivide K into data on IT and fewer still also have data on O or L^P. Thus it is very hard at the outset to measure the returns to k^{IT} and possible interactions with O. Second, even if one had such data, if O is endogenous and correlated with omitted variables in (3) or (4) then such returns and the marginal effects of potential interactions are biased. For example, if managerial quality is not measured and is in X and if better managers raise Y and also implement better O then α_2 would be upward biased in (3).[8] Thus it is hard to establish the contribution from O.

2.2 Existing evidence

What then is the approach of the literature to these questions? Bresnahan, Brynjolfsson and Hitt (2002) combine data on O, using a cross-section survey of managers in 1995, with the firms used in Brynjolfsson and Hitt (2003) who are observed between 1987-94. The data for these firms is on outputs, inputs and in particular, a lot of specific information on computer hardware. This leaves around 300 large US firms in their sample. They measure O as a linear combination of questions on team working, and the extent to which workers have authority over their pace and methods of work. Since O is a cross section, their main results are estimates of (3), where again they have no measures of L^O/L. They find statistically significant positive effects on Y_{it} from K^{IT}_{it}, O_{it} and $(O_{it} \bullet K^{IT}_{it})$ and emphasise the interaction between O and K^{IT}_{it}.

Black and Lynch (2004) obtain two cross-sections of data on O for 1993 and 1996, in their case indications of the use of high performance work systems, and combine this with a panel of firm data. Their data on K^{IT} is a questionnaire response as to whether non-managers use computers. Estimating both cross sections like (3) and panels like (4) they find that high performance workplace practices are associated with higher productivity and in particular that the share of non-managers using computers is positively correlated with productivity. Caroli and van Reenen (2001) have French firm data 1992-96. Their data on ΔO and Δk^{IT} are questionnaire responses on the use of new work organisation and use of new technology. Their main finding is that ΔO is statistically significantly associated with productivity growth particularly when interacted with skills but not significantly when interacted with their technology measure.

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[7] Strictly speaking, if (3) is translog (4) should include interaction terms between levels and growth. Here we are only trying to set out a broad description of what the current literature is aiming to do.

[8] Note in passing that the bias might be less serious in (4) to the extent that fixed aspects of managerial quality drop out; we shall work with changes in productivity below, but if unobservably more capable managers positively affect Δy and ΔO then a bias might still remain. Note too we shall examine whether ΔO interacts with Δk^{IT} *but not* Δk^{NIT} and argue that this is indeed the case. To ascribe the correlation between ΔO and Δk^{IT} wholly to endogeneity, it would have to be the case that there is an unobserved effect driving ΔO and Δk^{IT} but not Δk^{NIT}. Finally note we shall also present an equation explaining ΔO (competition).

There are of course a number of studies that look at highly related issues: either using O, but not IT, or IT, but not O. Boning, Ichniowski and Shaw (2001) study both the productivity impact of O and the determinants of O using data on physical output of US minimills for productivity and teamworking for O. In their study, teamworking boosts productivity and the decision to adopt teamworking is driven by things like plant characteristics (i.e. whether the plant is old or not), the complexity of the good produced and older and longer tenured managers. Their focus is not so much on IT however.[9]

Turning to the micro studies of IT without data on *O*, Brynjolfsson and Hitt (2003) assemble company level data on 527 US firms, over an 8 year period, 1987-94 (with some firms in the sample all the time and some not) with data on outputs, inputs and computers to estimate equations like (4) which they do using a mix of long and short differences. They have no measures of *O* or L^O/L however. They find long run returns to ΔK_{it} to exceed short run returns which they interpret as consistent with congruent changes in O. Using UK plant level data, Bloom et al. (2006) construct a panel of data on output and inputs, including IT and non-IT capital (as we discuss below, their data comes from a different source to ours). They have no data on O, but instead interact IT capital with a dummy if the firm is part of a US multi-national. In levels and differences such as (3) and (4), such a dummy is positive and significant, in IT-using intensive sectors (see their Table 1, columns 5 to 8). They interpret the dummy as being a measure of superior O in US firms.

There are also a number of macro studies who have data on IT without data on *O*. The most relevant to our work is Basu et al. (2003). They assume that L^O workers are used to build future *O* and hence ΔO=f(L^O). From (4), ΔO and Δk^{IT} are correlated and hence L^O is related to Δk^{IT}. Thus from (4)

$$\Delta y_{it} = \alpha_1 \Delta x_{it} + \alpha_2 \Delta l_{it} + \alpha_3 \Delta k_{it}^{IT} + \alpha_4 \Delta O_{it} + \alpha_5 (\Delta k_{it}^{IT} * \Delta O_{it}) - \beta \Delta\left(\Delta k_{it}^{IT}\right) \qquad (5)$$

i.e. measured TFP growth falls in periods of accelerating IT capital growth (i.e. $\Delta(\Delta k^{IT})>0$). This might explain, they argue, the slowdown in EU TFP growth if EU countries are in the initial stages of installing IT capital when there is accelerating net investment.[10]

A rather smaller literature is concerned with the determinants of *O* or ΔO. Nickell, Nicolitsas and Patterson (2001) focus on the determinants of ΔO_{it}, using data on 66 UK manufacturing firms over the period 1981-86 who report whether they (a) removed restrictive practices or not and (b) introduced new technology. They also use 98 firms who were surveyed in 1993/4 as regards changes in their management

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[9] There is of course a related literature that has no data on IT or on O but looks at a number of proxies that might determine O, most notably unions, product market competition or ownership. On unions for example Clark (1984) and Haskel (2005) find a negative effect on US and UK data, whilst Freeman and Medoff (1978) find a positive effect on productivity all of which is consistent with unions affecting O. On competition, Nickell (1996) finds a positive effect of increased competitive pressure on TFP growth, consistent with competition affecting O. On ownership, Doms and Jensen (1996) and Criscuolo and Martin (2005) find various effects on TFP of country of ownership, consistent with management affecting O.

[10] This argument is closely related to the investment spikes literature, see e.g. Power (1999), whereby it is argued that due to adjustment costs especially high investment leads to an initial fall in productivity. This approach here captures that idea, namely that increased capital, here in IT, requires organisational change, which in turn requires labour input

practices. They find that financial and market pressures, the latter measured by lagged changes in market share, are more likely to make firms introduce innovations in O. Caroli and van Reenen (2001) find that ΔO is correlated with relative wages and technology but they do not look at competition (they note this as a topic for future work, p.1482).

2.3 Our contribution

What then is our contribution? First, we assemble firm level data on almost 6,000 firms where we measure inputs and outputs, including Δk^{IT} and ΔO. Thus we add what is a rather larger data set to the relatively small extant evidence on this question. We have productivity growth data so we estimate (4) where we hope to control for what are potentially a number of unobservables in (3). Second, we also try to understand why some firms do and do not introduce ΔO. Our hypothesis is that ΔO is related to competition and hence we also estimate an equation for ΔO namely

$$\Delta O_{it} = \beta_1 \Delta COMPET + \beta_2 Z \qquad (6)$$

where $\Delta COMPET_{it}$ is a term to indicate increasing competitive pressure on the firm and Z_{it} are other terms which determine the firm's propensity to introduce ΔO. Included here will be ownership, specifically dummies indicating whether the firm is a US-owned multinational enterprise (MNE), foreign non-US owned MNE and UK-owned MNE (with UK domestic firms being the base category). This will allow us to examine whether MNEs of different ownership are more likely to introduce, other things equal, ΔO. [11]

3 Data

The data appendix gives full information on our data, which we summarise briefly here.

3.1 CIS data

Our main data are drawn from the Third Community Innovation Survey (CIS3), an official stratified survey of firms with more than 10 employees (omitting agriculture, fishing and forestry, public administration and defence, education, health and social work) with a 42% response rate. The questionnaire was posted in 2001 and gives productivity and ΔO activity between 1998 and 2000. Our data is at the line of business level, which for shorthand we refer to as a "firm". After extensive cleaning we have 5,944 firms in the sample, 3,019 in manufacturing and 2,925 in services.

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that takes them away from current production. Thus a "spike" in investment, or positive net investment, reduces measured LP and TFP growth. We find evidence for this "spike" effect, in terms of IT investment, in our data below.

[11] Below we also try to instrument IT using data on broadband penetration by region. Unfortunately, this turns out to be a very poor instrument. Hence the decision to invest in IT, likely an important function of the price of IT which may not vary across firms is not modelled here. The biases however may not be that severe: see footnote 8.

3.2 Data on ΔO

In trying to measure ΔO, Ichniowski and Shaw (2003, p.158) distinguish between a "scientific technology shock" and an "organisational technology shock". From the production function we might interpret this as a distinction between embodied and disembodied changes. Given how hard to measure this is, there are various measures in the literature. BBH for example use data on teamworking as their measure of O i.e. something that does not necessarily involve different capital; fast turn around of airliners by low-cost airlines might be another (as opposed to a computerised booking system to make reservations over the web which we might think of as an embodied technology). Black and Lynch (2003) define O as "workforce training, employee voice and work design (including the usage of cross-functional production processes)". Our survey questions on organisational change are as follows: "*Wider innovation. Did your enterprise make major changes in the following areas of business structure and practices during the period 1998-2000 and how far did business performance improve as a result?*" The options given were "*a. Implementation of new or significantly changed corporate strategies e.g. mission statement, market share, b. Implementation of advanced management techniques within your firm e.g. knowledge management, quality circles, c. Implementation of new or significantly changed organisational structures e.g. Investors in People, diversification, d. Changing significantly your firms marketing concepts/ strategies e.g. marketing methods.*". Firms are given four response options: "not used" and impact on performance "low", "medium" and "high".[12] We reduced each answer to a 1/0 (yes/no) since the impact part of the answer is too endogenous to the production function and might be driven by the subjective judgement of the respondent. Answers to (b) and (c) would appear to proxy changes in organisational capital in the firm. Answers to (a) and (d) are more difficult to interpret since they may or may not have involved changes in organisational capital. On the other hand, firms are asked (a) first which might affect their propensity to answer the other questions. For the moment, we combined them but we shall inspect the robustness of this below.

A number of points are worth making regarding this measure. First, the measure is clearly not ideal. Presumably, there are many aspects of a firm's O: teamwork, morale, consultation methods, lean production, family-friendly work practices etc. and thus any questionnaire is almost bound to provide only a partial measure, as BBH acknowledge. This suggests that it might be easier to try to measure ΔO, as we try to here, as opposed to the level of O. To the extent that this measure is noisy, it biases us away from finding a statistically significant effect. Second, in our data 58% and 51% of firms in manufacturing and services respectively reported implementing ΔO.[13] These answers refer to firms ticking any of (a) or (b) or (c) or (d) in the question. It turns out that 41% of firms that ticked any of the alternatives also ticked all boxes and 55% of firms answering yes to (a) answered yes to (b), (c) and (d). Indeed, there were very few firms who ticked only one or two or three of the boxes.

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[12] Note the question asks about major changes and so should exclude minor more routine changes in O.

[13] The weighted results are qualitatively similar, e.g. the weighted proportion of firms doing some organisational change is 0.48 (instead of 0.54). Weights are provided by the CIS to deal with stratification, but not with non-response.

Firms are in addition asked about what are called their technological innovations, called "process" and "product" innovations. We were concerned that process innovations might also incorporate disembodied re-organisation such as contracting out, new working methods etc. As the Data Appendix sets out in some detail, many firms who supplied a description of their (major) process innovation stated a description such as this. Thus we included process innovations as part of ΔO but tested as well for excluding them. As a matter of data, fewer firms report process innovation: 25% and 16% in manufacturing and services respectively. Thus as a whole, 63% and 54% of firms respectively implement both organisational change and/or process innovation.

3.3 Data on IT

We next require data on IT. The CIS data asks firms to report total investment in 1998 and in 2000. It then asks firms, in the section on innovation expenditure, to report expenditure on "*Acquisition of machinery and equipment (including computer hardware) in connection with product or process innovation.*" We use these data to measure the fraction of investment that we will call IT investment.[14] To verify the data, the Data Appendix documents a number of checks: first, these data are strongly correlated with IT-related text in the answers to the process innovation question; second, these data are also correlated with the industry share of IT investment constructed using two independent data sets; third, merging these data with the Annual Business Inquiry (ABI) production survey data and using the investment data to construct an IT and non-IT capital stock yields very similar results to US and UK results. Thus we regard this measure as one of advanced capital equipment and well correlated with IT investment.

We find an average of 0.021 for I^{IT}/Y and an average I^{IT}/I of 0.10. The ONS Volume Index of Capital Services project reports an average I^{IT}/I of 0.13 using their national accounts industry data (see Data Appendix). So our data compare well with this.

3.4 Data on output and other controls in the production function

To estimate the rest of (4) we require data on changes in output, employment and materials. As mentioned above, the CIS collects data on turnover and employment in 1998 and 2000; so we construct changes (of both output and all inputs) as two-year log differences. One might worry that firms answer this inaccurately and so we matched the CIS data with ABI data drawn in 1998 and 2000 to check.[15] The correlation coefficient between (logs of all variables) turnover on the CIS and the ABI data was 0.96 and 0.92 in 1998 and 2000 and for employment, 0.92 and 0.66. These correlations are reassuringly high, although the correlations on log changes in turnover, employment and labour productivity were lower at 0.46, 0.57 and 0.30. There are a number of points here. First, the CIS asks for FTE employment whereas the ABI data asks for headcounts. Second, as is well recognised in panel data work, a small amount of

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[14] The data appendix describes this. Briefly, we lack the data to construct Δk^{IT} and so we use (I^{IT}/Y) as a regressor, where I is investment in IT. To measure IT we use data from this question on IT above and to measure overall investment, we use questionnaire data on total investment. The appendix sets out a number of checks on the IT and investment data against other sources.

random difference between two levels might translate into a larger difference when changes in the levels are being considered.

Further, the CIS has no data on material use. Since materials constitute over 60% of gross output on average and changes in material use are positively correlated with investment (correlation of 0.20) on the ABI data, we felt it was important to try to include materials in our work. Thus for the around 1,000 firms who are both on the CIS and the ABI data we used materials as reported on the ABI data. For the other firms, we interpolated materials by using a linear regression of materials on turnover and other inputs, and inserted a dummy in the regressions where materials were interpolated.

Finally, firms are also asked about their product innovations, which we shall use as a control for unobserved changes in firm-specific prices. Firms are asked how much of their turnover is accounted for by product innovation; our data shows this to be around 7% of turnover.

We use these results in Table 1 to look at innovation by various dimensions: firm employment, labour productivity and IT use, where classification is relative to average employment, average labour productivity and average IT intensity in the relevant three-digit industry. As Table 1 shows, large, highly productive and high IT users all show higher fractions of the self-reported innovation measures. We also show ΔO by ownership status. US MNEs are most likely to implement ΔO, followed by UK MNEs and foreign MNEs, with domestic firms less likely to do so.

4 Econometric implementation and results of production function

4.1 Econometric implementation of the production function

Looking at (1), let us add to X, K^{NIT}, non- IT capital stock and M, materials. We do not have firm-specific price deflators, P_i, but industry-specific deflators, P_I, so that our measured real output is (P_iY_i/P_I). Hence we write (4) in log linear form with an interaction between ΔO and Δk^{IT}

$$\begin{aligned}\Delta y_{it} = \alpha_{11}\Delta k_{it}^{NIT} + \alpha_{12}\Delta k_{it}^{IT} + \alpha_2 \Delta O_{it} + \alpha_3(\Delta O_{it} \bullet \Delta k_{it}^{IT}) + \alpha_{41}\Delta l_{it} + \alpha_{42}\Delta m_{it} \\ -\alpha_5 \Delta(L^O / L)_{it} + \alpha_6 \Delta(p_{it} - p_{It}) + \varepsilon_{it}\end{aligned} \quad (7)$$

Moving term by term, we first have the question of how to measure Δk^{NIT} and Δk^{IT}. This is set out fully in the Data Appendix, section 5, but briefly, since we have data on investment, I, we enter (I^{NIT}/Y) and (I^{IT}/Y) respectively and interpret the coefficient as rates of return.[16] Second, terms in ΔO are discussed above. Third, measures of Δl come directly from the data and measures of Δm are interpolated from the ABI data as explained above. We do not have a direct measure of $\Delta(L^O/L)$ but look at this more in the robustness checks below. Fourth, we do not have plant level data to measure $\Delta(p_{it}-p_{It})$ but we do have data on whether

[15] The matched capital expenditure on the CIS and ARD are also similar.
[16] Since both I and Y are in nominal terms, these are gross rates of return and therefore include depreciation. Since IT is typically supposed to depreciate much faster than non-IT then one would expect these rates to differ. For our purposes our main interest is exploring the interaction with ΔO. It is also worth noting that since I^{IT} is measured worse than I^{NTT} it is likely that its coefficient is biased downwards.

the firm has introduced a product innovation and if so what share of output such an innovation accounts for which we use. We believe this to be of interest since as Bresnahan et al (2002) remark; the improved process due to IT is often used for improved products as well. Thus we can, to some extent, get some measure of the improved revenues controlling for improved products. Fifth, to control for industry effects, we express all variables in terms of their deviation from their three-digit mean. Finally, we include a number of other dummies: 12 regional dummies, λ_R and dummies for start-up and merger status, $\lambda_{S,\,i}$ (that might temporarily affect the output/input relation). Thus we estimate

$$\begin{aligned}\Delta(y-l)_{it} = \gamma_1(I^{NIT}/Y)_{it} + \gamma_2(I^{IT}/Y)_{it} + \alpha_2\Delta O_{it} + \alpha_3\Delta(O_{it} \bullet I^{IT}_{it}) - \alpha_{41}\Delta l_{it} + \alpha_{42}\Delta m_{it} \\ + \alpha_7 PROD\_INN + \lambda_R + \lambda_{S,i} + v_{it}\end{aligned} \quad (8)$$

where all variables are in deviation from their three-digit mean and we transformed the right hand side variable to be productivity growth. It is important to note that whilst the use of differences controls for fixed omitted factors, we have relegated $-\Delta(L^O/L)$ to the equation error. We discuss robustness to this below.

4.2 Results

Table 2 sets out the results of estimating (8). Column 1 shows the results excluding the interacted terms in ΔO. The marginal returns to $(I/Y)^{NIT}$ and $(I/Y)^{IT}$ are 0.21 and 0.30 respectively and the term in product innovation is significant. Column 2 adds the interacted $\Delta O \bullet (I/Y)^{IT}$ term. This is positive and significant at conventional levels with the coefficient on $(I/Y)^{IT}$ much reduced. Thus, this column has an interesting interpretation, namely that the measured marginal returns to IT investment are 12% with no organisational change, but an additional 23% with organisational change. Finally, column 3 adds an interaction between ΔO and the non-IT investment term, $\Delta O \bullet (I/Y)^{NIT}$. This is insignificant.

Taken together, these columns suggest significant returns to IT, extra returns to IT and ΔO performed together, that lower the measured returns to IT alone, and no extra returns to non-IT and ΔO performed together. All these findings are consistent with BBH's results for the US and suggest there is something particular about the relation between ΔO and IT investment rather than all types of investment.

How robust are these results? We investigated a large number of issues. First is the issue of outliers and influential observations. In working with a single cross-section of differenced data it is potentially important to examine if possible outliers might unduly influence our results (note that the outliers may or may not be "rogue" observations). Thus columns 4 to 6 of Table 2 control for influential observations using the method proposed by Belsey, Kuh and Welsch (1980).[17] As the columns show, this method removes 723

[17] The Belsey et al (1980) method focuses on each coefficient and measures the difference between the regression coefficient when the i^{th} observation is alternatively missing and included, the difference being scaled by the standard error of the coefficient. Following them, we identified influential observations as those observations whose deletion generates absolute changes higher than $2/\sqrt{n}$ in *any* of the explanatory variables in the regression. This method is more general than looking at, say, residuals, since it controls for large leverage. (Consider for example explanatory observations all clustered together bar one single outlying observation. OLS fits a regression line through this single

observations. The coefficients on $(I/Y)^{IT}$ and $(I/Y)^{NIT}$ fall somewhat, whilst the coefficient and statistical significance of the interacted $\Delta O \bullet (I/Y)^{IT}$ term rises. The interaction between $(I/Y)^{NIT}$ and ΔO remains non-significant. Thus our results are robust to removing influential observations, indeed are rather improved by this.

The second robustness check is to look at the relation for different industries. If IT is a general purpose technology, then we might expect its influence on productivity, controlling for ΔO to be pervasive. Columns 7 to 10 of Table 2 then explore these results by manufacturing and services and small and large firms. As these columns show, the differences between manufacturing and services and large and small firms for our key input and interacted $\Delta O \bullet (I/Y)^{IT}$ coefficients are small. More formally, we ran the basic regression interacting the $\Delta O \bullet (I/Y)^{IT}$ term with dummies for small firms in services, large firms in services and large firms in manufacturing, the omitted category being small firms in manufacturing. None of these dummies even approached statistical significance (results not reported but available from the authors).

The third robustness check is for the omission of $-\Delta(L^O/L)$. One way to control partially for this is to add $(Y/L)_{it-1}$ to (8). Firms with low levels of productivity in the previous period might have done so because they had high levels of L^O/L, which would affect their likelihood of changing L^O/L. In addition, quite apart from measuring omitted $-\Delta(L^O/L)$, including $(Y/L)_{it-1}$ might also control for transitory shocks to productivity due to e.g. measurement problems etc. or that firms with initially low levels of productivity have more opportunity to learn from other more successful ones, so raising productivity growth if such improvements are not measured in ΔO.[18] Also, this term might help control for the omitted capital intensity terms due to only having data on I and not Δk, see Data Appendix, section 5. Thus columns 1 and 2 of Table 3 add lagged productivity levels. This does not make too much difference to the interacted terms coefficients, but reduces their statistical significance somewhat.

Columns 3 and 4 try another possible variable to pick up $\Delta(L^O/L)$, namely investment accelerations. As discussed above in relation to the investment spike literature, if investment accelerations require additional staff time to implement, then they could proxy for $\Delta(L^O/L)$.[19] As the table shows, these terms are indeed negative, suggesting that measured TFP growth falls during investment accelerations. This is also consistent with the macro evidence cited above; see section 6 below for further discussion. Note the significance of the interacted $\Delta O \bullet (I/Y)^{IT}$ term remains.

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data point, which may not have a large residual but has a severe influence in the estimated coefficients which this method should detect).

[18] Note that because we are including industry dummies, lagged labour productivity captures the productivity gap between each plant and the technological frontier (since the frontier is absorbed by the industry effects).

[19] The dummy for investment accelerations is built as follows: (i) we compute the investment rate for each plant in each year between 1998 to 2000, where *current* investment is normalized by using *current* turnover, (ii) we compute the average investment rate for each firm over the three considered years and (iii) we define that we observe an investment acceleration if the current investment rate in year 2000 is larger than the average investment rate. Note that this definition of investment acceleration is very close to the idea of investment spikes used in the empirical literature of lumpy investment models (see Power, 1998 for example).

The fourth robustness check concerns the use of survey data. It might be felt that firms do not answer such surveys well, particularly when firms are asked to recall turnover, investment and employment from two years ago. To explore this, we took the CIS sample of 5,942 used above and matched them to ABI data, leaving us with 1,008 observations that have complete output, employment and materials data in 1998 and 2000. It is worth noting however, that the matched firms are mostly in manufacturing and are large since the ABI data are mostly for larger firms. Since the ARD does not ask IT investment until 2001, we use the CIS IT data as in the regressions above. The results are set out in columns 5 to 7 of Table 3. The coefficients on $(I/Y)^{IT}$ are similar, although the $\Delta O \bullet (I/Y)^{IT}$ terms falls in insignificance, perhaps due to the preponderance of manufacturing firms in the data.

Finally, we undertook a number of other robustness checks (not reported in full, available on request). We added two skills measures, specified the ΔO to be the wider innovation term, used the BBH standardised measure, namely the standardised sum of the standardised answers but all these left the $(I/Y)^{IT}$ and $\Delta O \bullet (I/Y)^{IT}$ terms largely unaffected.[20]

5 Econometric implementation and results of ΔO equation

5.1 Econometric implementation

Our estimating equation for ΔO builds on (6) and can be written

$$\Delta O_{it} = \beta_1 \Delta MSHARE_{it-1} + \beta_{21} MULTIPLANT_{it} + \beta_{22} SIZE_{it-1} + \beta_{23} MNE_{it} + \lambda_I + \varepsilon_{it} \tag{9}$$

where $\Delta MSHARE_{i,t-1} = (Y_i/Y_I)_{1998} - (Y_i/Y_I)_{1997}$, *MULTIPLANT* is a dummy valued at 1 if the firm is part of a larger group and 0 otherwise $SIZE_{t-1} = \ln L_{i,1998}$, and recall that ΔO is defined between 1998 and 2000. MNE is a vector of three separate dummies taking the value one if a US MNE, a foreign non-US MNE or a UK MNE. We also experiment with a dummy for exporting, where exporters are only domestic non MNE firms who export. λ_I are five-digit industry dummies.

A number of points are worth making. First, concerning the measurement of competition, we wish to measure changes in the intensity of competition, since ΔO is the dependent variable. As noted by Nickell (1996) current levels of market share are likely endogenous to current O, where a high level of O would lead

[20] If we use the BBH standardised method applied to our ΔO variables in our productivity growth regressions we obtain coefficients on ΔO and $\Delta O \bullet (I/Y)^{IT}$ of -0.002 (t=0.75) and 0.04 (t=1.21). For comparison, they find 0.02 and 0.02 (in their productivity level regressions). It is worth remarking on the finding that ΔO is hardly statistically significant in any results and sometimes (insignificantly) negative. One possibility is that the 1/0 nature of the variable is too discrete to capture what is likely very different scales of ΔO between different firms, but when interacted with I/Y^{IT} it attains some scale. The other possibility is that, as theory suggests, it is biased by the omission of $\Delta(L^O/L)$. There is some moderate support for this from the regressions that include the lagged productivity level and the investment acceleration term. Here the ΔO term, whilst remaining negative, tends to zero and shows a considerable increase in its standard error, suggesting that when some controls for this omitted variable are included, the ΔO term moves toward its theoretically predicted sign.

to high MSHARE. Lagged changes however should be a reasonably good measure of increased competitive pressure on firms and so (9) is interpreted as saying that a past reduction in market share is symptomatic of increased competitive pressure which raises the subsequent probability of implementing ΔO. Thus we expect a negative co-efficient on $\Delta MSHARE_{i,t-1}$ in (9) and since endogeneity bias would give a positive coefficient, the estimated co-efficient is likely a lower bound on the true effect.

Second, we wish to use lagged $\Delta MSHARE$. We have Y_i and L_i in 1998 on the CIS but the earliest period where we have Y_I for manufacturing and services from the business register is 1997. So $\Delta MSHARE_{i,t-1}$ is a change between 1998 and 1997 i.e. the first period of the CIS and the year before it. Third, the share of the three digit (we also experiment with four and five digit) industry is a share of a market defined on the supply side, since SIC industries are implicitly defined as collections of firms with higher elasticities of technical substitution. Much competition analysis however looks at markets as defined on the demand side with high elasticities of demand substitution. With almost 6,000 firms we simply cannot undertake analysis of the demand side for each firm and so have to make do with this measure. Fourth, a new entrant in 1998 does not of course have a market share for 1997 so we set their change equal to their market share in 1998, while for the rest of unmatched firms we imputed the variation in the market shares using their size and sector medians (when we worked only with the matched sample we obtained the same results).[21]

What is the theoretical rationale behind (9)? We think of it as a reduced form describing two basic approaches to the determinants of O. The first might be to regard O as reflecting knowledge capital and competition forces firms either to invest in more acquiring such capital or to use such inputs more effectively. A second way of viewing O is that organisational capital also includes the organisation of work which can be summarised by the effort that workers apply to tasks. In models of effort under imperfect competition (see e.g. Haskel, 1991 and Nickell, Wadhwani and Wall, 1992) workers bargain over wages and effort with firms who have some product market power. With tighter product market competition, under certain conditions, workers raise their bargained effort.[22]

5.2 Results

Table 4 shows the results of estimating (9) (by probit since ΔO_i is a 1/0 variable, and in the table we report marginal effects). Note the number of observations is 5,944 as before but shows up as 5,926 in the table since we include five-digit dummies that perfectly explain some of the observations. Column 1 shows the marginal effect of $\Delta MSHARE_{it-2}$ where the only other controls are five digit industry dummies, 12

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[21] In the regressions below where we use changes in market share we add a dummy for imputed observations. We also experimented with lagged growth, since slow growing firms might be more inclined to invest in ΔO since the opportunity cost of labour taken away from production to so invest is lower when sales are lower. Or, they are less inclined to invest in ΔO if such changes, which might conceivably involve job loss, are more acceptable to workers in growing companies (where employment would grow by less than it would otherwise do, but at least not fall). In fact, lagged growth was positively signed and significant and improved the t statistic on ΔMSHARE.

regional dummies, 3 dummies for start-up/merger status and a dummy for the cases where we have to impute $\Delta MSHARE_{it-2}$ (the result are robust to omitting this). The $\Delta MSHARE_{it-2}$ term is negative, indicating that falling market share between 1997 and 1998 makes firms more likely to introduce ΔO between 1998 and 2000. The coefficient is significant at the 30% level. Column 2 adds a multiplant dummy MULTI to control for economies of scale and scope in introducing ΔO. This is very significant and the effect of $\Delta MSHARE_{it-2}$ strengthens somewhat. Column 3 introduces log employment (in 1998), which also shows economies of scale and scope but renders the effect of MULTI insignificant; importantly however, it further strengthens the effect of $\Delta MSHARE_{it-2}$. Thus this very austere specification supports the idea that increased competition makes firms introduce organisational change. As noted above, the effect when using lags is more revealing of the true causal effect (which of course we cannot estimate without a natural experiment) since using current data would likely induce a positive correlation as firms introducing ΔO_i likely grow market share. Since the endogeneity bias likely biases the effect toward being positive, the true causal effect is likely more negative than the negative effect that we find.

Column 4 adds the MNE dummies: the results are most interesting. Looking at the coefficients, relative to domestic firms (the omitted category), US, non-US and UK MNEs are 10%, 7% and 3% more likely to introduce ΔO (with the last effect insignificant). This is consistent with the idea that these firms can transfer information from other plants (in this case in other countries) and so introduce ΔO. Lastly column 5 adds the lagged exporting dummy and here finds that the marginal effect from exporters and UK MNEs is about the same. It is worth noting that these effects are economically significant too, with US MNEs 15% more likely to introduce ΔO than, for example, UK domestic firms.

6 Other checks

6.1 IV and systems estimation

We used the determinants of ΔO in (9) as instruments for ΔO in the productivity growth equation (8) The simplest method, which turns out to be representative, is to use $\Delta MSHARE$, $SIZE$ and the MNE dummies from Table 4, column 4 as instruments for the ΔO and $\Delta O \bullet (I/Y)^{IT}$ terms in Table 2, column 5. The results of this are reported in Table 5 column 2 (column 1 repeats the baseline result for comparison). The coefficient on ΔO is positive, contrary to the OLS term, and that on $\Delta O \bullet (I/Y)^{IT}$ is also positive of lower magnitude than the OLS effect and not well determined. Column 3 obtains very similar results using iterative 3SLS.

What is the interpretation of these results? There are a number of points. First, as the Table shows, the Hausman test was never significant, indicating that our IV results were never significantly different from the OLS results. Second, as Stock and Staiger (1998) point out, IV results are biased toward OLS results if

[22] The conditions essentially depend upon worker preferences over wages and effort: if workers' marginal disutility from increases in effort are sufficiently large and their disutility from falls in wages is sufficiently small then workers might agree steep enough wage cuts in the face of increased competition to be able to take effort reductions too.

the instruments have little explanatory power. However, as the Table shows, our first step F tests returned F values above 10 so we do not think that this is driving the closeness of the OLS and IV results. Third, our instruments were valid as tested by the Hansen J statistic. In sum, we do not claim that our OLS results are true causal effects, but rather that for the choice of instruments we have here (which statistically are reasonably strong), the OLS results are statistically the same as our IV results. Finally, we estimated the two equations as a SURE system, and as column 4 shows, the coefficients are not much changed from the OLS results.

Finally, it is worth remarking that we did try to find instruments for the decision to invest in IT due to the fact that under complementarity this decision should be taken simultaneously with the decision to carry out organisational change. The problem, however, is to find convincing instruments for an investment variable like this in a cross section sample. We try with different alternatives such as using information about the IT infrastructure in the district where the firm is located (e.g. if there is broadband access at the firm postal address) or if the firm is located in one of the so-called "assisted areas" for business support. None of these alternatives rendered satisfactory results: typically the instrument was not well correlated with IT investment. The consequences of this, in our context, might not be too serious however. First, as BBH note, our results confirm the complementarity idea that investment in IT also requires complementary ΔO investment. Second, the coefficient on the IT term in the production function does not appear to produce implausible returns. Third, it is unlikely that our results are entirely due to unobserved managerial ability since that would affect both Δk^{IT} and also Δk^{NIT}.

6.2 Ownership

We have three further comparisons with other work. As mentioned above, Bloom, et al. (2006) estimate firm-level regressions of output on IT capital, non-IT capital, labour and materials. They have no data on ΔO, so they interact their IT capital terms with a dummy for multi-national enterprise (MNE) status. Their key finding with respect to this paper is that US MNEs have a positive and significant interactive (US_MNE$\bullet k^{IT}$) term in levels and with fixed effects for IT-Using intensive sectors (see their Table 1, columns 4 and 7). They argue that US ownership proxies better organisational and specifically managerial capital at the firm.

How does this (US_MNE$\bullet k^{IT}$)effect compare with our $\Delta O\bullet(I/Y)^{IT}$ effect here? Recall that we find a positive $\Delta O\bullet(I/Y)^{IT}$ effect on productivity growth and also a positive effect of US MNEs on ΔO. Thus there are (at least) two interpretations. The first is that US MNEs perform more ΔO, and hence the Bloom et al (2006) paper is a reduced form. The second is that in addition to MNEs performing more ΔO, their ΔO has a higher marginal impact than in non-MNEs. We look at these issues in Table 5 column 5 which drops the ΔO and $\Delta O*(I/Y)^{IT}$ terms and replaces them instead with US_MNE and US_MNE*(I/Y), where US_MNE is a dummy taking the value 1 if the firm is owned by a US company and zero otherwise. The new terms have just the same pattern as in Bloom et al (2006), namely an insignificant effect from US_MNE (recall the dependent variable is productivity growth so this is consistent with a significant effect on productivity levels) but a positive and almost significant interacted $US\_MNE*(I/Y)^{IT}$ term.

Column 6 adds back in the ΔO and $\Delta O*(I/Y)^{IT}$ terms. Statistically speaking, the $\Delta O*(I/Y)^{IT}$ term has a lower standard error than the $US\_MNE*(I/Y)^{IT}$ term. Thus one interpretation of their results is that US_MNE does indeed proxy ΔO. Another possibility is that there is an additional effect, namely that not only do US MNEs undertake more ΔO, but that the marginal impact of such ΔO is greater in a US MNE that in other organisations. This is setting our data a strong test, but we explored this in column 7 by interacting $\Delta O*(I/Y)^{IT}$ with the US_MNE dummy. The result is intriguing, with a positive and significant at 10% effect of both $\Delta O*(I/Y)^{IT}$ and also $\Delta O*US\_MNE_{it}*(I/Y)^{IT}$. Taken literally, the returns to IT, from column 4 are 12% with no ΔO for non-US firms, 31% (0.1236+0.2054) for IT investment undertaken with ΔO for non-US firms and 90% (0.1236+0.2054+0.5882) for IT investment with ΔO for US firms. Perhaps uncovering these exact numbers is placing too much strain on our data (although recall that these are gross returns for IT capital that include depreciation which is often measured at 33% for computers), but nonetheless we believe that our results complement the Bloom, et al. (2005) work and support their argument that the unmeasured factor behind the MNE dummy in their paper is superior organisational capital.[23]

6.3 Competition

Papers such as Nickell (1996), Disney, Haskel and Heden (2001) enter lagged $\Delta MSHARE$ directly into the production function, with no measures of IT or ΔO to test if changes in competition affects productivity growth. To compare with their results we dropped the ΔO and $\Delta O*(I/Y)^{IT}$ terms in (8) and replaced them instead with $\Delta MSHARE_{it-1}$ and $\Delta MSHARE_{it-1}*(I/Y)^{IT}$ where we expect both terms to have a negative sign since the relation between ΔO and $\Delta MSHARE_{it-1}$ is negative. We obtain coefficients of: -0.014 (t=1.48) and -0.84 (t=1.26) respectively, which are signed consistently with the other work. The implied elasticity at sample mean is 0.02%, lower than the implied elasticities of between 2% and 4% in the Nickell (1996) and Disney et al (2001) papers, but as Disney et al (2001) show using a 12 year panel, the elasticity falls as the number of panel years falls due to selection effects.

Finally, instead of dropping the ΔO and $\Delta O*(I/Y)^{IT}$ terms and replacing them with $\Delta MSHARE_{it-1}$ and $\Delta MSHARE_{it-1}*(I/Y)^{IT}$ if we include ΔO and $\Delta O*(I/Y)^{IT}$ and simply add the $\Delta MSHARE_{it-1}$ and $\Delta MSHARE_{it-1}*(I/Y)^{IT}$ terms we obtain the following coefficients and t statistics; respectively -0.0087 (1.71), 0.24(3.44), –0.015 (t=1.54) and –0.73 (t=1.08). An F test for the two latter additional terms for $\Delta MSHARE_{it-1}$ and

[23] There is a slight complication in comparing our results to their interacted results with fixed effects. Since we estimate in differences, and use ΔO, the closest comparison to their work is their levels regressions with fixed effects. All their input terms are specified as deviations from four digit industry means. Thus their interacted term with fixed effects represents the interaction of MNE status with the deviation from the company average relative input level, where the relative input level is relative to the 4 digit industry mean. Variation in this measure can occur with changes in IT investment relative to the firm-industry average with no change in MNE status and also changes in MNE status with no change in investment.

$\Delta MSHARE_{it-1}*(I/Y)^{IT}$ suggests they can be excluded from this regression. Along with the finding that ΔO is affected by $\Delta MSHARE_{it-1}$ this is consistent with the interpretation that the production with just $\Delta MSHARE$ in it is a reduced form describing that rising competition raises organisational change and so productivity growth.

6.4 Organisational change, IT and the UK slowdown in productivity growth

We started the paper with the observation that the literature aims to better understand the business process of translating IT to productivity, the TFP growth slowdown in Europe and why some firms institute ΔO and some not. We may use our production function to get some sense of the first two questions by, following BBH, simulating the impact on productivity growth of firms who implement ΔO and IT investment to different extents. To do this, we calculate the implied change in *per annum* TFP growth when firms are either high or low in their implementation of ΔO, (I/Y) and $\Delta(I/Y)$ (using column 4 of Table 3, where high and low refers to firms at the 90^{th} and 10^{th} percentiles of the relevant distributions). Consider first then a firm who is at the 90^{th} percentile of the distribution of firms doing ΔO, (I/Y) and $\Delta(I/Y)$. Such a firm has *fall* in measured TFP growth of productivity of 0.85% per year. The reason of course is the negative effect of the $\Delta(I/Y)$ term. Thus we might interpret this as showing the extent of the productivity slowdown in a firm in, for example, the initial stages of IT implementation when investment is necessarily large to move to a desired capital level. A firm who does not implement ΔO (strictly is at the 10^{th} percentile of ΔO) suffers a measured TFP growth fall even more of 1.25% pa. Finally, firms implementing ΔO and (I/Y) but with no acceleration in investment have a *rise* in TFP growth of 0.75% pa.

How do these numbers compare with the macro numbers? Basu et al, (2003 table 5) document a fall in UK gross output TFP growth in what they call their well-measured industries of 0.79% pa between 1990-95 and 1995-2000. This slowdown seems consistent with the predicted slowdown from our micro data for firms in the first stages of IT implementation both with and without organisational change (slowdowns of 0.85% pa and 1.25% pa respectively). To compare this, Basu et al (2003, table 4) document a speedup in US gross output TFP growth in well-measured industries of 0.62% pa between 1990-95 and 1995-2000. If we interpret the US economy as one implementing ΔO and investing in IT at a steady rate, this number compares quite well with our results at the micro level (of 0.75% pa). Finally, using data for the UK, Oulton and Srinivasan (2005) suggest that the acceleration in investment in IT lowered TFP growth by 0.45% pa (although investment capital deepening raised TFP growth by 0.85% per annum).

7 Conclusion

This paper has used data for UK firms to examine the relation between productivity growth, IT investment and organisational change. Consistent with the small number of other micro studies we find (a) IT appears to have high returns in a growth accounting sense when one omits ΔO, but when ΔO is included the IT returns are greatly reduced: (b) IT and ΔO interact in their effect on productivity growth; (c) There is no impact on productivity growth from ΔO and non-IT investment. Some new findings are (a), we find that ΔO is affected by competition and (b) US-owned firms are much more likely to introduce ΔO relative to other MNEs and exporters who are more likely still relative to UK domestic only firms, (c) our numbers seem to compare quite well with the macro evidence in documenting a UK measured TFP growth slowdown. Of course one should be cautious about these results given measurement error and the attendant difficulties of empirical work. But they support the idea that gains from IT need re-organisation to produce measured productivity growth and that initial IT investment slows measured productivity growth down. Our results also support the idea that US MNEs undertake more organisational change others things equal. This suggests that the UK slowdown relative to the US is a combination of later IT investment and less organisational change, the latter which might be due to less competitive pressure.

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Table 1: Organisational change and firm's characteristics

		Observations	Proportion with ΔO=1
	Relative to 3-dig industry mean		
Size(t-1)	Above	2,691	0.11
	Below	3,253	-0.09
LP(t-1)	Above	2,806	0.03
	Below	3,138	-0.02
IT	Above	1,091	0.23
	Below	4,853	-0.05
Ownership			
US MNE		191	0.80
Non US MNE		413	0.75
UK MNE		495	0.76
Domestic		4,845	0.54
Total		5,944	0.58

Note: The first row is the unweighted proportion of the whole sample who implemented organisational change. To construct the middle top panel of the table we calculate the three digit average of row and column variables. The cell reported is the average of the deviation from the three-digit average of the row variable for all firms classified by the column variable. Thus the second row right cell says that firms who are above average lagged size, with the average being taken relative to the three digit lagged size, have implemented organisational change 11 percentage points above the three-digit industry mean organisation change. The bottom panel shows the average fraction of firms who have implemented organisational change for each ownership category, where MNE stands for multi-national enterprise.

Source: Authors' calculations using CIS3

Table 2: Regressions estimates of productivity growth equation (8)

(dependent variable $\Delta\ln(Y/L)_{it}$, all variables measured as deviation from three-digit mean)

	1	2	3	4	5	6	7	8	9	10
	All obs	All obs	All obs	Drop infl obs	Drop infl obs	Drop infl obs	Manuf	Svs	Small	Large
$\Delta\ln L_{it}$	-0.5782	-0.5778	-0.5783	-0.5662	-0.5664	-0.5666	-0.5521	-0.582	-0.5824	-0.5354
	[20.56]***	[20.55]***	[20.62]***	[53.98]***	[54.02]***	[54.03]***	[36.81]***	[39.52]***	[45.02]***	[28.81]***
$\Delta\ln M_{it}$	0.2553	0.2552	0.2552	0.2652	0.2651	0.2652	0.2638	0.2661	0.2734	0.2482
	[12.06]***	[12.06]***	[12.07]***	[37.07]***	[37.08]***	[37.09]***	[26.08]***	[26.11]***	[30.79]***	[20.03]***
$(I/Y)^{NIT}_{it}$	0.2085	0.2074	0.15	0.1514	0.1509	0.1354	0.175	0.1308	0.1297	0.1781
	[5.24]***	[5.21]***	[2.07]**	[9.28]***	[9.25]***	[5.70]***	[7.53]***	[5.70]***	[6.26]***	[6.57]***
$(I/Y)^{IT}_{it}$	0.2991	0.1179	0.112	0.2466	0.0773	0.075	0.1365	-0.0222	0.0297	0.1212
	[3.64]***	[1.73]*	[1.62]	[6.75]***	[1.37]	[1.33]	[1.99]**	[0.18]	[0.37]	[1.87]*
$\Delta\ln p_{it}-\Delta\ln p^{I}_{t}$	0.065	0.0623	0.0614	0.0559	0.055	0.0548	0.0506	0.0588	0.0266	0.0962
	[2.13]**	[2.03]**	[2.01]**	[3.47]***	[3.40]***	[3.39]***	[2.30]**	[2.48]**	[1.23]	[3.99]***
ΔO_{it}	-0.0072	-0.0101	-0.0187	-0.0052	-0.007	-0.0088	-0.0083	-0.0054	-0.0041	-0.0082
	[0.75]	[1.03]	[1.59]	[1.07]	[1.39]	[1.50]	[1.15]	[0.77]	[0.64]	[0.93]
$\Delta O_{it}\ (I/Y)^{IT}_{it}$		0.2349	0.2395		0.2009	0.2034	0.1355	0.3194	0.2192	0.1916
		[1.98]**	[2.01]**		[2.89]***	[2.92]***	[1.59]	[2.24]**	[2.23]**	[2.12]**
$\Delta O_{it}\ (I/Y)^{NIT}_{it}$			0.0911			0.0227				
			[1.21]			[0.76]				
Observations	5944	5944	5944	5221	5221	5221	2717	2504	3297	1924
R-squared	0.3	0.3	0.3	0.43	0.43	0.43	0.4	0.45	0.45	0.38
F-Stat	25.49	24.41	23.52	159.6	152.81	146.12	74.29	82.19	105.55	48.82
RMSE	0.31	0.31	0.31	0.16	0.16	0.16	0.16	0.16	0.16	0.16

Note: Robust t-test in brackets, equations include 12 regional dummies, dummy for start-up and dummies for imputed inputs and organisational change. The impact of influential observations is controlled by using the method proposed by Belsey, Kuh and Welsch (1980) see text.

Table 3: Robustness checks of Table 2: add lagged productivity levels, investment accelerations and use ABI data

(Dependent variable $\Delta\ln(Y/L)_{it}$, all variables measured as deviation from three-digit mean)

	1 CIS data	2 CIS data	3 CIS data	4 CIS data	5 ABI data	6 ABI data	7 ABI data
$\Delta\ln L_{it}$	-0.5557	-0.5554	-0.5581	-0.5583	-0.7974	-0.7974	-0.7974
	[19.74]***	[19.73]***	[52.05]***	[52.09]***	[15.88]***	[15.87]***	[15.84]***
$\Delta\ln M_{it}$	0.2437	0.2435	0.2615	0.2614	0.4089	0.4092	0.4091
	[11.56]***	[11.56]***	[36.62]***	[36.63]***	[12.88]***	[12.88]***	[12.86]***
$(I/Y)^{NIT}_{it}$	0.1787	0.1778	0.1506	0.15	0.2316	-0.4195	-0.4218
	[4.58]***	[4.56]***	[9.17]***	[9.13]***	[1.95]*	[1.07]	[1.06]
$(I/Y)^{IT}_{it}$	0.2477	0.0857	0.2464	0.0907	0.18	0.1794	0.2161
	[3.08]***	[1.32]	[6.69]***	[1.62]	[2.83]***	[2.82]***	[1.56]
$\Delta\ln p_{it}-\Delta\ln p^{I}_{t}$	0.0748	0.0723	0.0577	0.0569	0.0849	0.0851	0.0855
	[2.45]**	[2.36]**	[3.58]***	[3.52]***	[1.70]*	[1.70]*	[1.71]*
ΔO_{it}	-0.0008	-0.0034	-0.0024	-0.0041	-0.013	-0.016	-0.0108
	[0.08]	[0.35]	[0.50]	[0.81]	[0.80]	[0.96]	[0.49]
$\Delta O_{it}\ \Delta(I/Y)^{IT}_{it}$		0.2101		0.1844		0.6708	0.6735
		[1.82]*		[2.68]***		[1.63]	[1.62]
$\Delta O_{it}\ (I/Y)^{NIT}_{it}$							-0.0481
							[0.34]
$\Delta(I/Y)_{it}$			-0.0154	-0.0151			
			[3.37]***	[3.29]***			
$\ln(Y/L)_{it-1}$	-0.0475	-0.0473	-0.013	-0.013			
	[4.97]***	[4.95]***	[3.33]***	[3.34]***			
Observations	5944	5944	5221	5221	1008	1008	1008
R-squared	0.31	0.31	0.43	0.43	0.70	0.70	0.70
F-Stat	24.58	23.59	146.88	141.16			
RMSE	0.31	0.31	0.16	0.16	0.22	0.22	0.22

Note: Robust t-test in brackets, equations include 12 regional dummies, dummy for start-up and dummies for imputed inputs and organisational change. Columns (1) and (2) control for lagged labour productivity, Columns (3) and (4) controls for investment accelerations and lag labour productivity. Columns (5) to (7) controls use ABI data on Y. L, M.

Table 4: Probit estimates of ΔO equation (9)

(dependent variable ΔO, 0/1 variable, estimation by probit, numbers here are marginal effects)

	1	2	3	4	5
$\Delta MSHARE_{it-2}$	-0.0298	-0.0325	-0.0757	-0.0754	-0.0743
	[1.01]	[1.13]	[1.97]**	[1.95]*	[1.94]*
$Multiplant_{i}$		0.1188	-0.003	-0.0023	0.0021
		[7.44]***	[0.17]	[0.13]	[0.12]
lnL_{it-2}			0.0989	0.093	0.0864
			[15.99]***	[14.06]***	[12.92]***
US_MNE_{i}				0.1047	0.1496
				[2.30]**	[3.32]***
$Non\_US\_MNE_{i}$				0.074	0.1169
				[2.40]**	[3.75]***
UK_MNE_{i}				0.0256	0.0706
				[0.87]	[2.35]**
$Exporter_{it-2}$					0.0967
					[5.27]***
Observations	5926	5926	5926	5926	5926
PR2	0.14	0.15	0.18	0.18	0.19
Chi2	870.15	904.32	1026.88	1021.3	1050.92
LL	-3463.62	-3436	-3299.05	-3294.13	-3280.25

Note: Robust Z test in brackets, equations include five digit industry dummies, dummy for imputed market shares, dummy for start-up, 12 regional dummies and a constant.

Table 5: The effect of ownership and ΔO on productivity growth: OLS and IV

(dependent variable $\Delta \ln(Y/L)_{it}$), all variables as in Table 4, column 5 included, only those variables shown reported, all variables measured as deviation from three-digit mean)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	2SLS	i3SLS	SURE	OLS	OLS	OLS
ΔO_{it}	-0.007	-0.0322	-0.0287	-0.0083		-0.0113	-0.0108
	[1.39]	[1.47]	[1.32]	[1.58]		[1.14]	[1.09]
$\Delta O_{it}\ (I/Y)^{IT}_{it}$	0.2009	0.1031	0.2235	0.1785		0.2094	0.2054
	[2.89]**	[0.17]	[0.38]	[1.47]		[1.74]*	[1.71]*
US_MNE_i					0.0163	0.0188	
					[0.67]	[0.76]	
$US\_MNE_i\ (I/Y)^{IT}_{it}$					0.563	0.5115	
					[1.66]*	[1.49]	
$\Delta O_{it}\ US\_MNE_i\ (I/Y)^{IT}_{it}$							0.5882
							[1.85]*
Observations	5944	5221	5221	5221	5944	5944	5944
R-squared	0.31				0.31	0.31	0.31

Note: Robust t-test in brackets, All variables measured as deviation from three-digit mean. Outliers removed. Tests and P values for IV equations in column 2 and 3 are: Hansen tests (Hansen/Sargan test of instrument validity from regression of residuals on assumed exogenous variables), 10.5 (p=0.23), Hausman test (test of whether the IV and OLS coefficients are significantly different), 2.17 (p=0.11), First step test (test for the significance of the instrument in a regression of the endogenous variable on the instrument and other exogenous variables), for ΔO_{it} 30.65 (p=0.00), for $\Delta Oit \bullet (I/Y)^{IT}_{it}$ 22.38 (p=0.00). Column 4 is estimation by SURE, other columns are by OLS. Column 1 repeats Table 2, column 5.

Data Appendix: Further details on the CIS data and ΔO, IT and other variables.

A1. The CIS

The CIS is a voluntary postal survey carried out by the Office of National Statistics on behalf of the Department of Trade and Industry, co-ordinated by Eurostat. ONS randomly selects a stratified sample of firms with more than 10 employees drawn from the Interdepartmental business Register by SIC92 2-digit class and 8 employment size bands. The CIS is voluntary and postal. To boost response, enterprises are sent the survey, posted a reminder, posted a second reminder (with the survey again) and finally telephoned. The response rate is 42% (about 8,000 questionnaires are returned), which is quite respectable against other voluntary surveys. The survey is conducted at the "enterprise" level; where enterprise is defined as "the smallest combinations of legal units which have a certain degree of autonomy within an enterprise group". Thus the survey potentially refers to more than one plant/establishment but it does refer to distinct lines of business. For shorthand we shall refer to the unit of response as a "firm".

A2. Data on ΔO

We wish to gather data on disembodied organisation change. The embodied/disembodied distinction seems suited to our data, since the CIS opening questionnaire paragraph says

> *We begin by looking at innovation based on the results of new technological developments, new combinations of existing technology or utilisation of other knowledge held or acquired by your enterprise….The final part of the questionnaire broadens the focus to consider organisational and management changes.*

The actual question on organisational innovation, Question 17, refers to the latter part of this sentence and is as set out in the main body of this paper. The question on process innovation is

> *5. Process Innovation.*
>
> *"For this survey process innovation is the use of new or significantly improved technology for production or the supply of goods and services. Purely organisational or managerial changes should not be included. For examples of process innovations see front cover"*
>
> *During the three year period 1998-2000, did your enterprise introduce any new or significantly improved processes for producing or supplying products (goods or services) which were new to your firm?*

The examples of process innovations on the front of the questionnaire are as follows:

> *EXAMPLES OF PROCESS INNOVATIONS*
>
> *Linking of Computer Aided Design station to parts suppliers*
> *Introduction of Electronic Point of Sale equipment in Garden Centre*
> *Digitising of pre-press in printing house*
> *Robotised welding*

Firms are also given an example of what is *not* an innovation

> *EXAMPLES WHICH ARE NOT TECHNOLOGICAL INNOVATION*

> *The renaming and repackaging of an existing soft drink popular with older people, to establish a link with a football team in order to reach the youth market, is not a technology based innovation as defined in this survey, but could register as a marketing change in question 17. New models of complex products, such as cars or television sets, are not product innovation, if the changes are minor compared with the previous models, for example offering a radio in a car.*

A number of points are worth making here. First, the examples of team working or turnaround times of airliners seem to be non-technological and so according to the question, potentially captured by the "wider innovations" in Question 17 above. A computerised booking system is more likely a technological process innovation as defined by the questionnaire; see the examples that are specified to firms, but in terms of the production function, likely embodied in capital. Since firms are then asked about their expenditures on machinery related to innovations, then this expenditure likely captures expenditure on advanced capital, much of which is likely to be IT and we shall use this below. Thus if they are captured in ΔK^{IT} and ΔK^{NIT} then this suggests they might not be included in ΔO.

Second, it is quite possible that such process innovation, even if it is just expenditure on advanced machines, also involves disembodied organisational change as well which we would wish to capture. In the regressions below we therefore use both measures and also them separately, but to probe this further at this stage we undertook two more detailed investigations.

The first investigation to shed light on just what a process innovation is to look at what firms said they did by way of process innovation. After being asked whether or not firms had a process innovation firms are asked

> *5.4 Please give a short description of your most important process innovation:*

We used these answers to try to analyse what firms mean when answering yes to a process innovation: are they reporting on IT, other types of machines or organisational change. What did we find?

Around 1200 firms responded "yes" to having done any sort of process innovation but only 874 provide some description of it. To analyse what they say systematically we searched each description firms entered for any word we thought to be related to the hardware part of information technologies (IT) investment (key words used were: *computer/s, automation, automatic digitalisation, Cnc, digital, automated, robotic, cad, networking, digitising, PC, computerisation, it, cam, network, robot, hardware, satellite, robotisation and automating*.) These key-words were generated after the analysis of a random sample of about 100 reported process innovations. We then generated a new dummy variable called HARDWARE if any of these words was present.

We then applied the same procedure to generate a dummy variable called SOFTWARE to detect the software component of information technologies, using the keywords*: website, email, online, on-line, internet, web, software, virtual, programming, e-commerce, edi, cctv, programmes, application, intranet and email*.[24] Finally, we applied the procedure to generate a PROCESS ORGANISATION dummy, with keywords *outsourced, coding, bar, lean, cell, sourcing, management, planning, outsourcing, laying out, iso, just, layout, cellular, logistics, kanbam, kanbams, stock and re-organise*. Finally, for those cases with no match with any of the above mentioned key words, we created a category called "NON-IDENTIFIED". Inspection of this category included typically complex descriptions of advanced capital machinery (for example: installation of steel wire armouring machinery, improved petal and leaf cutting, precision cooking and slicing equipment, introduction of spectrophotometer for more accurate shade matching).

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[24] In this case some text cleaning was required because there were several cases with the phrase "computer software", which was cleaned to just "software".

Appendix Table 1 shows the results of this analysis.[25] The largest category is still the non-identified case with 53% of the cases. Looking at the other categories, about 22% are hardware related process innovations, 15% are software related process innovations and less than 9% correspond to process organisation. Thus it would seem reasonable to assume that whilst many reported process innovations are machinery related, especially to IT, at least some of the reported process innovations are possibly disembodied since they refer to new sorts of the organisation of production, perhaps linked to the introduction of new machines.

Appendix Table 1: Analysis process innovation using firm-reported text

Type of Word	Number	Share (%)
HARDWARE word	197	22.54
SOFTWARE word	134	15.33
LEAN PROCESS word	78	8.92
NON-IDENTIFIED	465	53.20
Total	874	100

Source: Authors' calculations using CIS3

Our second investigation is to look at the correlations between reported process innovations, IT spending[26] and reported organisational innovations. Appendix Table 2 sets out all the possible combinations of IT, organisational change and process innovation. Thus this does not confine us to just those firms who answered yes to process innovation and then filled out the most significant innovation.

Appendix Table 2: IT investment, Process Innovations and Organisational Change

Type of Innovation	Number	Share (%)
No IT, no OCH, NO Proc	2,136	36
Yes IT, no OCH, no Proc	340	6
No IT, Yes OCH, no PROC	1,540	26
No IT, No OCH, Yes Proc	116	2
Yes IT, Yes OCH, No Proc	729	12
Yes IT, No OCH, Yes Proc	133	2
No IT, Yes OCH, Yes Proc	283	5
Yes IT, Yes OCH, Yes Proc	667	11
Total	5,944	100

Source: Authors' calculations using CIS3. Numbers may not add due to rounding.

As the table shows, the largest group (36%) are those who did none of all three questions. The second largest are those doing just organisational change (OCH) (26%), but not either of the two other changes. The third largest (12%) are those investing in IT and OCH but claiming to have no process innovations, whilst 11% of firms are making changes in all three dimensions. All the other categories are below 6% of firms.

What then is the interpretation of these numbers? First, the largest group, those who did only organisational change with no process or IT investment (25.9% of firms), is consistent with the idea that reported organisational change is potentially disembodied from IT capital. Second, 7.71% of firms report

[25] Because there was some degree of overlapping among the different classes, some results were re-allocated in order to have classes that are fully exclusive. If there was an overlap between HARDWARE and SOFTWARE the observation was allocated only to SOFTWARE, because it is the class with fewer cases. Following in the same way, if there is an overlap between SOFTWARE and LEAN the observation was allocated only to the last one, and so on. Hence, in the results of below the categories will be fully exclusive.

[26] We set out how we measure IT below.

doing process innovation but no spending on IT (1.95 with no organisational change, 5.76 with) suggesting that, as above, at least part of process innovation might not necessarily be embodied in IT capital.[27] Third, 12.26% of firms undertook IT and OC but reported no process innovations. These might be firms whose IT is not related to the technical production process but needs OC e.g. payroll, accounting or customer records e.g. IT. Fourth, can we enter organisational change and process innovation as separate measures of ΔO? Since we will enter IT as well identification of these measures separately would rely on sufficient firms undertaking them in isolation.[28] The problem is that, as Appendix Table 2 shows, only 1.95%of firms undertook only process innovation with no organisational change or IT investment. Thus we are not confident that we can enter organisational change and process innovation as separate measures of ΔO and identify them reliably (this indeed turned out to be the case, both terms and their interactions were ill determined because of multi-collinearity). Therefore we combined them together as part of ΔO. [29]

A3 Data on IT

To cross-check the data on IT we did the following. First, as documented in the answers to the questions above, many firms responded to the process innovation description questionnaire with IT related descriptions and many with specialised capital machinery. Thus we believe that answers to this question are likely at least to relate to advanced capital machinery and frequently to IT investment.

Second, to check this further, we undertook a similar text analysis this time for all firms who reported a process innovation and also reported spending on machinery (620 firms, as opposed to the 874 reporting a process innovation in Appendix Table 1. The patterns of analysis were very similar to Appendix Table 1 with the fractions reporting hardware, software, process organisation and non-identified being 24%, 14%, 7% and 55% respectively.

Third, we cross-checked our data against two industry-level IT estimates The first is available at roughly two digit level and comes from the VICS project at the ONS which calculates the volume of capital services for two digit industries from 1970 to the present. It does this by calculating capital stocks for buildings, vehicles, IT machinery and non-IT machinery using perpetual inventory methods and weighting these together by the user cost of capital for each stock. We obtained the investment data for each series and expressed nominal IT investment as a proportion of total investment, where total investment was the total nominal investment in all categories, not weighted by the user cost (this is therefore the closest to what we do).

Appendix Table 3 sets out the results. The top row shows, by two digit industry, the number of observations, the average ratio of nominal IT investment to total nominal investment, the standard deviation, the minimum and maximum for our measure. The second row shows the data from the VICS database. As the table shows, the mean value and standard deviation are very close, although the minimum and maximum are rather larger in our data. The final two columns show the Pearson and rank correlations, which are statistically significant.[30] Thus we conclude our measure correlates quite well.

For our second comparison, we compiled three-digit industry averages from our data and compared them with those derived from the firm-level dataset used in Bloom et al. (2006). The lower panel of Appendix Table 3 shows the results. Here the average value is higher than in the first panel but the averages look similar.[31] The final two columns report significant correlation coefficients.

Fourth, we have a smaller sample of data where we can match the CIS to ABI data on outputs and inputs, including total capital stock data.[32] Using the CIS data on IT investment and non-IT investment, we

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[27] This calculation is done by setting any missing values for IT equal to zero. There were under 10% of these and deleting these altogether made little difference.

[28] This is not strictly correct since we use IT as a continuous variable as set out below. But it gives the essential intuition behind why in practice we cannot identify all these effects separately.

[29] When we entered these variables together they were too collinear to be precisely estimated.

[30] These numbers are after deleting 3 outlier industries that rendered the correlation statistically insignificant.

[31] It is not clear why the averages higher than in the upper panel, but could be to do with the weighting on the industry panel (the lower panel is unweighted) and different use of micro data in the industry data.

[32] The ABI collects detailed data on outputs and inputs but on investment inputs not capital stock, see Criscuolo, Haskel and Martin (2003). We build up capital stocks using investment data and an assumed starting value using the perpetual inventory method, see Martin (2004).

built an IT and non-IT capital stock for this sample, 1997 to 2000 giving us 2,804 firm-year observations. We then ran a regression of the log level of value added on the levels of employment, non-IT capital and IT capital (with additional controls for three digit industry dummies, regional dummies, year dummies and company status change dummies). We compared these coefficients with those reported by BBH, Table 6 column 1, who have 3,331 firm-year observations; the coefficient on IT capital was 0.030 (t=3.07) whereas BBH obtained 0.033 (t=1.99). Thus this robustness check produces very close results to them and this is especially interesting given that their IT measure is based on a survey of hardware computing power.

Fifth, Bloom et al (2005) report a share of IT in gross output of 0.012 (see their table 1). When we undertake the above regression on gross output rather than value added, the coefficient on the log level of IT capital is 0.0055. The implied marginal return to IT capital is 0.0055/0.012=46%. Below we shall find a marginal return of 30%, which seems not too far from this estimate, given our estimate comes from an equation in first differences, which would bias down the estimated marginal return in the presence of measurement error.

Sixth, BBH suggest that IT, organisational change, upskilling and product innovation are all inter-linked. The correlation between all these variables (controlling for industry) was significant and positive in all cases.

Overall then, these seven robustness checks suggest to us that our data is correlated with advanced capital equipment and IT and thus, we believe, can be regarded as a (perhaps noisy) estimate of IT investment.

Appendix Table 3.: CIS vs. ONS IT Data, summary statistics and correlations

Survey	Agg Level	Obs	Mean	Sd	Min	Max	Pearson	Rank
CIS 3	Sic-Frame	18	0.107	0.081	0.010	0.335		
ONSa	Sic-Frame	18	0.126	0.084	0.001	0.280	0.546*	0.494**
CIS 3	Sic-3 Digit	43	0.127	0.104	0.011	0.456		
ONSb	Sic-3 Digit	43	0.149	0.093	0.034	0.504	0.546*	0.474**

Source: ONSa data comes from the Volumne Index of Capital Services (VICS) Database and ONSb data comes from Bloom, Sadun and Van Reenen (2006)

Finally, we are now in a position to reprise the question of what, on these data, constitutes a process innovation. Our maintained hypothesis, from the analysis of the text, is that it is a combination of advanced capital investment and process organisational change (e.g. lean manufacturing). IN fact the data shows that whilst 20% of firms report a process innovation 75% of firms report positive investment, so that process innovation is not just investment. 31% of firms report investment in IT, closer to the process innovation proportion, but still above it, confirming that IT investment can be more than just related to new manufacturing production processes. Thus we think these are data consistent with the view that measured process innovation is investment into advanced capital stocks and accompanying organisational change.

A4. Construction of Δ(I IT/Y) and Δ(I non-IT/Y)

We have data for I in 1998 and 2000 and data for IIT in 2000. We construct (I^{IT}/I) for 2000 and apply this to I in 1998 to get I^{IT} for 1998. We then interpolate these data for 1999. Accumulating those gives (I^{IT} /Y) for use in the regression, where Y is measured as output in 1998.

A5. Construction of Δk^{IT} and $\Delta k^{non\text{-}IT}$

In the regressions above we use I/Y in productivity growth regressions. The alternative is to use I and an assumed depreciation rate and starting value of K to calculate K with the perpetual inventory method. We set out a comparison of the two methods here.

Our CIS data is on investment and we can use it as follows. Using the relation $\Delta K=I-\delta K_{t-1}$ we may write $K^{00}=I^{00} + (1-\delta)I^{99} + (1-\delta)^2K^{98}$ where the superscript denotes the year. Since we have changes in Y between 1998 and 2000, we wish to measures changes in capital, Δk (ignore the IT and non-IT distinction for the moment). Using this equation, $(K^{00} - K^{98}) = I^{00} + (1-\delta)I^{99} - \delta(2-\delta)K^{98}$. There are then two ways to proceed. First, from the linearised production function, the output elasticity $\alpha=(\partial Y/\partial K)(K/Y)$. Hence we can write $\alpha\Delta \ln K=\gamma\ (\Delta K/Y)$ where $\gamma=(\Delta Y/K)$ which is the return on capital. Thus from the above, $(\Delta K/Y)= (I^{00} + (1-\delta)I^{99})/Y- \delta(2-\delta)(K^{98}/Y)$. The first term of this is data and so can be included in the regression. The last term is missing, since we have no initial capital stock value, K^{98} and so is omitted. Thus the bias to the estimated return depends on both δ and (in a single regressor model at least) the ratio of the covariance between $(I^{00} + (1-\delta)I^{99})$ and (K^{98}/Y).

An alternative method is to assume a value for K^{98}, the initial capital stock, and then use it to calculate $\Delta \ln K$ in (7) directly. We can write $\Delta \ln K=(K^{00} - K^{98})/ K^{98} = (I^{00} + (1-\delta)I^{99})/K^{98} - \delta(2-\delta)$. With an assumed value for K^{98} the first term on the right hand side is data, and the second term can be relegated to the equation error. The problem is that we do not have an initial value and our data set is too short for errors in an initial value to depreciate away. Hence we are forced with this approach to assume a missing value, in which case the omitted term consigned to the error is a function of the gap between the assumed and true value of K^{98} and $(I^{00} + (1-\delta)I^{99})$ (since K^{98} is in the denominator of the $\Delta \ln K$ expression). We were concerned that the assumption of a starting value could be hazardous, particularly since we do not even have total capital stock levels for all firms from the ABI data.

Since our concern is mostly with obtaining an expression for $\alpha\Delta \ln K$, we shall stick to using the investment ratios. However, we did wish also to compare our coefficients on inputs to those of Bresnahan who runs a *level* regression of lnY on logs of inputs (as well as levels of organisational capital). Thus to do this we needed to start with a measure for K^{98}. We did this by going to the ARD data and using the data there on the *total* capital stock of the firm. This is in turn calculated from a perpetual inventory method using ABI data on total investment (we have no data on IT investment in the production Census), which itself needs starting values for total capital stock, which we impute using two digit real ONS capital stock data multiplied by the share of materials spending in the firm as a proportion of total industry materials spending (we also impute investment data for years in which the firm is missing from the ARD sample). We then multiply this real capital stock for the firm by the fraction of all capital in the industry accounted for by IT according to the VICS data set to give us a real IT capital stock, the rest being non-IT capital stock. The biases in this method are therefore due to the possible inaccuracy of the starting IT capital stock value.

Appendix Table 4: Descriptive Statistics of main variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Y_{it}	5944	31480	251068	7	11200000
L_{it}	5944	195	891	1	42900
M_{it}	5944	16967	124228	1	6634977
$\Delta\ln(Y/L)_{it}$	5944	0.062	0.375	-4.779	3.320
$\Delta\ln L_{it}$	5944	0.059	0.345	-3.769	2.803
$\Delta\ln M_{it}$	5944	0.052	0.643	-6.413	6.971
$(I/Y)^{NIT}_{it}$	5944	0.097	0.150	0.000	0.953
$(I/Y)^{IT}_{it}$	5944	0.021	0.069	0.000	0.862
$\Delta MSHARE_{it-2}$	5926	0.008	0.241	-6.62	8.548

Note: Y_{it} is the total turnover in 2000 (market sales of goods and services including exports and taxes except VAT) in £000. L_{it} is the number of employees (full time equivalents) in 2000. M_{it} is the total purchases of material and intermediate inputs in £000 (variable derived from the administrative records). $\Delta\ln(Y/L)_{it}$ labour productivity growth between 1998 and 2000. $\Delta\ln L_{it}$ is employment growth between 1998 and 2000. $\Delta\ln M_{it}$ is raw materials growth between 1998 and 2000. $(I/Y)^{NIT}_{it}$ is the IT investment rate over the period 1998-2000 normalized by turnover in 1998. Finally $(I/Y)^{NIT}_{it}$ is the Non-IT investment over the period 1998-2000 normalized by turnover in 1998. All the monetary figures are in current prices. $\Delta MSHARE_{it-2}$ is the variation of firm market share between 1997 and 1996 from administrative data

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