Network Effects and Productive Externalities from ICT and Knowledge Capital

Peter R. Goodridge
(Imperial College, UK)

Jonathan Haskel
(Imperial College, UK)

Harald Edquist
(Ericsson Research)

Paper prepared for the 35th IARIW General Conference

Copenhagen, Denmark, August 20-25, 2018

Session 6A-1: Skills, Employment and Productivity II

Time: Friday, August 24, 2018 [09:00-12:30]

Network effects and productive externalities from ICT and knowledge capital*

Peter Goodridge[†], Jonathan Haskel[‡], Harald Edquist[§]

February 19, 2018

Abstract

In previous work (Goodridge et al., 2016a) we have documented the contribution to growth of ICT equipment, and in particular communications (CT) equipment, in the US and Europe over the period 1995 to 2013. In this paper, using the same dataset, we seek to estimate whether there is also an indirect effect from growth in ICT capital input on growth in total factor productivity via network effects (or spillovers) over a similar time period. In doing so, we disaggregate ICT equipment into IT and CT capital, and attempt to estimate distinct effects from each. Our model also incorporates potential spillovers from activity in R&D. We find: a) evidence of a robust correlation between growth in ICT capital services and growth in TFP, which is consistent with network effects or spillovers, implying an output elasticity over and above the share of ICT capital costs in production; b) that disaggregation of ICT equipment creates two collinear variables, so we are unable to determine conclusively whether the ICT effect is driven by CT equipment, IT hardware, or both; c) that the correlation is stronger when taking longer differences, which is consistent with measurement error in the observed explanatory variable causing a downward bias to the estimated coefficient; d) that the estimated contribution of CT spillovers potentially explains around 50% of TFP growth in North European and Scandinavian countries, but overexplains TFP growth in the US (and South European countries, which have negative TFP growth).

Keywords: spillovers, network effects, telecommunications, ICT, R&D, externalities, growth, TFP
JEL classification: O47, O38, O32

*We are grateful for financial support from Ericsson Research, ESRC (Grant No.: PSB112_MSRH) and EPSRC (Grant No.: PSB111_MSRH). Errors and opinions are our own.

†Imperial College Business School, Imperial College London; South Kensington Campus, London SW7 2AZ, United Kingdom; p.goodridge10@imperial.ac.uk

‡Imperial College Business School, CEPR and IZA; j.haskel@imperial.ac.uk

§Ericsson Research, Ericsson Research, Färögatan 6, SE-164 80, Stockholm, Sweden; harald.edquist@ericsson.com

1 Introduction

Numerous studies have sought to measure the contribution of ICT to growth. In previous work (Goodridge et al., 2016a) we have estimated the separate contributions of distinct types of ICT capital (IT hardware equipment, communications (CT) equipment and software), with a focus on CT equipment, to labour productivity growth (LPG) in a growth-accounting framework across fourteen countries, with varying assumptions on the true rate of change in ICT investment prices. However, if communications networks generate network (or spillover) effects, then there may be an additional contribution, or an excess return, from CT equipment implicit within growth in total factor productivity (TFP).

According to Metcalfe's Law, the value of a network increases exponentially in proportion to the square of the number of connected users. As noted in Corrado (2011a), one way of thinking about the internet is as a (very large) piece of communications capital equipment, building on older telecoms capital and augmented by broadband and mobile technologies. When we consider the role and ubiquity of the internet in business activity and processes, and the innovations in how it is used, the extent to which CT capital contributes to growth may be much greater than the private contributions estimated in growth decompositions imply.

There are two broad reasons to consider that capital deepening in ICT equipment,[1] and in particular CT equipment, may be beneficial for growth in TFP. First, ICT is an input to the innovation process, used in the creation of new business models, intellectual property (IP) and other forms of knowledge capital. The latter may include new organisational capital in the form of the re-engineered business processes or improved managerial practice, made possible with the use of ICT capital. The ubiquitous nature of ICT as a general purpose technology (GPT) means that while the contribution of, say, R&D, is largely confined to manufacturing, ICT and complementary intangible capital contributes to growth in all sectors of the economy, including services where the contribution of R&D as traditionally measured is considerably smaller.[2]

Second, ICT may make an additional contribution in that these new ideas, practices and innovations may diffuse to other units in the wider economy. The extent and speed of diffusion may be enhanced by ICT, and in particular CT, equipment, which improves the abilities of organisations to network, co-operate, and transfer information and knowledge.[3]

Thus we can describe any excess effect from ICT capital accumulation on productivity growth (over and above its growth-accounting contribution) in two broad ways: first, its use in the innovation process, enhancing productivity via the re-organisation of production and the development and application of complementary intangible capital; and second, as the diffusion of those new successful ideas or practices to other firms and/or industries (externalities) (Basu et al., 2003).

We look for evidence consistent with each effect although, like Basu et al. (2003), our method does not provide a means to disentangle these complementary, related effects. In particular we seek evidence specific to CT and IT equipment (a number of studies omit CT from their ICT measures, while others aggregate it into ICT but do not consider it separately) but also control for effects from R&D, as well as software and

[1] In this paper, references to ICT capital refer to IT hardware, CT equipment and software. References to ICT equipment refer to IT hardware equipment and CT equipment.

[2] As R&D is composed of basic and applied scientific research, private R&D is largely conducted by firms in manufacturing, which account for around half of UK market sector R&D investment (Goodridge et al., 2014).

[3] We note a complementarity here with another aspect of ICT-related investment: data. Deeper, improved communications networks enhance the abilities of connected users to: share and transmit data and information; and communicate and implement the knowledge or insights extracted from data. To the extent that investments in data are currently under-recorded in the national accounts ((Goodridge and Haskel, 2015a);(Goodridge and Haskel, 2015b)), we would expect some part of their contribution to be present in TFP growth. This is another reason why we might expect a correlation between growth in telecoms capital and growth in TFP.

other forms of intangible capital. We note from the above descriptions that we would expect such effects to operate with some lag, as also noted in Basu et al. (2003) and various papers from Brynjolfsson (e.g. Brynjolfsson and Hitt (2003)), with the lag interpreted as either the time taken for spillovers to diffuse, or time to allow for the creation and contribution of co-investments in complementary intangibles.

The key lesson learned from research into the contribution of IT hardware was that accurate measurement of real investment and capital services required use of quality-adjusted deflators (see for example Triplett (2004)). In cases where national practice is to not develop country-specific hedonic deflators, researchers (or in some cases, national statistical institutes (NSIs)) have favoured the US Bureau of Economic Analysis (BEA) hedonic index or some version adjusted for that country, or sets of harmonised deflators across countries such as in EUKLEMS (Timmer et al., 2007). This way, measures of price change reflect improvements in power and other characteristics (speed, memory etc.), as well as falls in listed prices, and measured capital services better reflect changes in the real quantity of capital available for production.

Regarding technical progress in CT equipment, Doms (2005) notes that the pace of progress in fibre-optic capacity has been well above Moore's Law, with capacity doubling every year between 1996 and 2001. Clearly a telecoms investment price index must take this pace of change into account. In our estimation of CT (and ICT) capital services[4] and TFP, we apply consistent, harmonised estimates of price change across countries (Schreyer and Colecchia, 2002),[5] so that our results are not dependent on, or affected by, variation in the data and methods applied by individual NSIs.[6]

Our method of estimation is to regress growth in TFP on lagged growth in capital services, as in for instance Stiroh (2002) (although he uses contemporaneous ICT measures rather than lagged), and we control for potential omitted variables such as private and public R&D, software and other intangible capital. The first is an important control: Acharya and Basu (2011) note that it is essential that one controls for R&D. With R&D included they do not find evidence of ICT spillovers, but when they exclude R&D they do find an ICT effect. Thus they conclude that controlling for R&D is essential to prevent against incorrectly ascribing R&D spillovers to ICT spillovers. In our estimation we also seek a correlation between growth in TFP and growth in capital services from aggregate ICT equipment, noting that investments in these assets may be bundled such that some investments in CT equipment are still implicit within data for IT hardware. We work with both short and long differences, and we follow Goolsbee (2000) in using the respective estimates to correct the coefficient for measurement error in the explanatory variable, with the (downward) bias being more pronounced when working with shorter differences.

Our dataset is a panel of fourteen countries: the US and thirteen European countries, 1990-2013.[7] Unlike Stiroh (2002) who works at the industry-level,[8] we explore correlations at the whole economy level, which seems appropriate in the context of the hypothesis of spillovers to telecommunications network users due to the deepening or expansion of the entire network.

Controlling for time and country effects, we report a statistically significant correlation between growth

[4] Capital services for each ICT asset are estimated separately, with asset-specific investment prices and rates of depreciation.

[5] ICT asset price indices for each country are harmonised with those produced by the US BEA. We thank Vincenzo Spiezia of the OECD for sending us these data.

[6] However, robustness checks show that our results are similar when we estimate capital services and TFP using the ICT deflators implicit in each country's national accounts.

[7] Countries included are determined by availability of data from OECD.Stat. The panel is not fully balanced. For some countries our TFP data begin later than 1990.

[8] Data availability issues mean that his analysis focuses on manufacturing industries. As noted in that paper, many of the more ICT-intensive industries, in terms of ICT-use, lie outside manufacturing.

in ICT capital services and growth in TFP. In terms of statistical significance, disaggregating ICT equipment into IT hardware and CT equipment creates two collinear variables, leaving us unable to conclusively determine which is driving our ICT result.

In terms of economic significance, our results imply an (adjusted) excess elasticity of output to growth in CT capital of 8.6%.[9] We describe this as an excess elasticity since it is the effect on value-added growth over and above the direct contribution estimated via growth-accounting.[10]

Our paper is related to Corrado (2011b). Using an alternative method, she finds evidence of CT spillovers that explain around a third of US growth in TFP over the period 2000-07. Koutroumpis (2009) finds that around one-tenth of annual output growth can be attributed to increased broadband penetration. Our comparable figures are that: a) 113% of TFP growth in our 14-country aggregate (i.e. US and EU-13, 1990-2007) can be explained by growth in CT capital services; and b) 4.4% of growth in value-added per hour can be explained by the direct contribution of growth in CT capital deepening (1990-2013) (Goodridge et al., 2016a). Combined, these two estimates suggest that, on average, 29% of labour productivity growth in the US and EU-13 can be explained by growth in telecoms capital services.

The rest of this paper is set out as follows. Section 2 sets out our model in the context of the existing literature and section 3 sets out our data and method. Section 4 presents our results and section 5 discusses the economic significance of our results. Finally, section 6 concludes.

2 Model and existing literature

2.1 Model

Suppose that to get connectivity, economic agents first, buy capital to access to the network (phones, computers etc.), but second, also rent network services. Consider then an economy with two sectors: (a) a downstream consumption sector, which buys access capital, but rents (network) services; and (b) a telecommunications sector, which provides network services. We consider each sector in turn.

2.1.1 Downstream sector

The gross output of a firm in the consumption sector is assumed to be described by:

$$G_i^C = F^G(X_i, Z_i, A^C) \tag{1}$$

which says that the gross output of firm i depends on inputs X (labour, capital and intermediates), Total Factor Productivity (TFP) denoted$A$, and connectivity services, denoted Z. Suppose Z_i has three elements. First, firms have to obtain access to the network: suppose they purchase (access) capital equipment to do this (a phone, internal switching gear, computer) denoted byK^{ACC}. Second, they have to rent network services,N (the network infrastructure connected to the access capital). Third, the connectivity services of firm i depend on the connectivity of others: if there is congestion this might have a negative marginal effect, with Metcalfe's law it might rise (say with the square of connections). Thus we write Z as:

$$Z_i = F^Z(K_i^{ACC}, N_i^{NET}, Z_{-i}) \tag{2}$$

[9] That is, a 1% increase in growth in CT capital services would raise output growth by 0.086%.

[10] The CT-output elasticity as conventionally measured (by its factor share) in 2013 varies from 0.13% in the UK to 1.3% in Austria. On average, for the fourteen countries in our dataset, in 2013 the CT income share was 0.6%.

Let us write this technological relation in terms of log changes as (where lower case letter denote logs and dx is the change in lnX):

$$dz_i = \varepsilon^Z_{K^{ACC}} dk_i^{ACC} + \varepsilon^Z_{N^{NET}} dn_i^{NET} + \gamma^Z dz_{-i} \tag{3}$$

and so in a symmetric equilibrium

$$dz = \frac{\varepsilon^Z_{K^{ACC}}}{(1-\gamma^Z)} dk^{ACC} + \frac{\varepsilon^Z_{N^{NET}}}{(1-\gamma^Z)} dn^{NET} \tag{4}$$

which shows that the flow of connectivity services to all those connected depends on the own-elasticity of access and network services scaled by the effect from the network externalities, $1/(1-\gamma^Z)$. If there are congestion externalities then $\gamma < 0$,in which case the own-elasticities are scaled down $((1/(1-\gamma^Z)<1)$. By contrast, if there are positive network externalities then $\gamma > 0$, in which case the own-elasticities are scaled up $((1/(1-\gamma^Z)>1)$.[11]

Suppose further that firms purchase access and network services competitively, in which case the elasticities are the share-weighted cost of such services. Thus log differentiating equation (1), substitution of (4) and replacing the elasticites by their shares, and forming a gross output weighted sum over all downstream firms gives, for the downstream C sector:

$$dg_i = \sigma^C_X dx^C + \frac{\sigma^C_{K^{ACC}}}{(1-\gamma^Z)} dk^{ACC} + \frac{\sigma^C_{N^{NET}}}{(1-\gamma^Z)} dn^{NET} + da_i^C \tag{5}$$

where σ are shares of downstream gross output. Notice that due to the network effects, the effect on output of the components of communications services is greater than its payment share (if $0 > \gamma > 1$).

2.1.2 Communications/network industry

We turn now to the network services industry which produces network capital services from the network capital stock K^{NET}, inputs (labour) $X^{NET}$and technology A^{NET}:

$$N_i^{NET} = F^{NET}(X^{NET}, \mu_i K^{NET}, A^{NET}) \tag{6}$$

which is to say that the flow of network services to firm i depends on network capital times a factor μ, where μ most naturally captures utilisation of the network. [12]If we assume that the network services industry is regulated to competitive prices then it chooses X and K such that:

[11] We also need $\gamma < 1$ i.e. that from equation (3), an individual's percentage rise in connectivity services following a percentage rise in the connectivity of others is not more than 100%.

[12] The approach of multiplying the network capital by a utilisation factor contrasts with the Berndt-Fuss-Hulten (1986) approach, which is to specify the production function in terms of variable inputs (here X) and quasi-fixed inputs (here K). In that model, any utilisation effects are captured not by adjusting K by a μfactor, since by assumption the production function depends upon the stock of quasi-fixed inputs (see e.g. Berndt and Fuss (1986) equation (10) and the discussion immediately below). However, the rental price of those quasi-fixed inputs has to be amended since a quasi-fixed factor will be rented at a shadow input price reflecting quasi-rents, not the market input price (and as long as there is only one quasi-fixed factor, the ex post user cost method will correctly identify that shadow price). As they note in their footnote 10, one can always instead adjust the quantities of quasi-fixed factors using the competitive factor price: given that many networks are regulated to competitive prices and then subsidised this seems an acceptable way forward. On the equivalence, suppose capital is variable and labour is quasi-fixed such that in booms, workers work overtime at a rate $P_L(1+o)$. Thus one can write the production function in terms of labour services, here hours, paid for at $P_L(1+o)$. Or one can write the production function in terms of persons, paid for at at price Z which is above the competitive rental rate P_L.

$$dn_i^{NET} = \sigma_X^{NET} dx^{NET} + \sigma_{K^{NET}}^{NET} (d\mu_i + dk^{NET}) + da^{NET} \tag{7}$$

where we have replaced the output elasticities by their factor shares with no mark-up, which is appropriate for an industry optimising in the face of regulated output prices.

2.1.3 Economy value added and TFP growth

To the firm i, payments for rental of network services are intermediate spending, whereas payments for access capital are expenditures on durable capital at the firm. Define nominal value added in the C sector implicitly as $P^G G^C = P^V V^C + P^N N$ (which says that gross output in the the downstream is the sum of value-added and intermediates). Construction of an appropriate price index for value-added means that $dg^C \equiv s_{V^C}^{G^C} dv^C + s_N^{G^C} dn^{NET}$. Define economy-wide value added growth as $dv \equiv s_{V^C}^V dv^C + s_N^V dv^N$ where $dv^N = dn^{NET}$ since there are no intermediates in the network providing sector by assumption. Substitution gives:

$$dv \quad = \sigma_X^V dx + \tfrac{\sigma_{K^{ACC}}^V}{(1-\gamma^Z)} dk^{ACC} + \tfrac{\sigma_{N^{NET}}^V}{(1-\gamma^Z)} (d\mu + dk^{NET}) + da \tag{8}$$

where da is the share-weighted sum of the sector technology terms. Economy-wide TFP growth is measured by subtracting from output growth share-weighted input growth giving:

$$dtfp^V \quad = \quad da + \frac{\gamma^Z}{(1-\gamma^Z)} \left(\sigma_{K^{ACC}}^V dk^{ACC} + \sigma_{K^{NET}}^V (d\mu + dk^{NET}) \right) \tag{9}$$

Equation (9) suggests a number of points. First, the components of connectivity affect TFP growth due to the externality, γ. As above, if there is congestion on the network, $\gamma < 0$ and TFP growth is slowed with more network use: with no congestion, TFP growth accelerates. Second, the network effect is multiplied by the share of spending on access capital and network capital. This is in contrast to many models of externalities in growth-accounting where TFP growth is assumed to be affected by growth in some variable, dx, rather than share-weighted growth, as is the case in the R&D literature for example. This is because the externalities work via the purchase of communications services: that is, $Z_{\_i}$ appears in equation (2) and not in (1). If it appeared in equation (1) directly, then there would be no need to share-weight, since it is assumed that externalities work directly on production and not indirectly via the purchase of communications services. The appearance in equation (2) means that connectivity externalities only appear conditional on the purchase of such services, hence the share-weighted term in equation (9).

How reasonable is it to assume that $Z_{\_i}$ appears in (2) and not in (1)? One might argue that benefits can accrue without being connected e.g. a non-connected firm expecting a delivery benefits from a connected set of trucks. However, such a benefit would show up in the price and thus not be a TFP benefit. It might also be that some network benefits are priced in, in the sense that regulators often allow some network externality to mobile phone prices at least, in which case the effect would not show up in TFP growth at all.

Third, notice from equation (9) that TFP growth is also affected by changes in utilisation, $d\mu$, since the flow of capital services from a built-out network will depend upon how intensively the network is used. That intensity might be proxied by, for example, fractions of the population connected, or, fractions of the population using broadband, variables that are often used in studies. If this variable is capturing utilisation, then it is not strictly a network effect. Notice that it is quite possible that μ is actually close to 1: for example, mobile mast networks are typically built only when demand justifies them.

Fourth, notice that we have to be careful with our interpretation of the shares, σ. Firms and consumers are both sources of network externalities, and are both purchasers of access capital. In national accounts however, household purchases of durable goods are *not* counted as investment, and hence the measured share of access capital purchases only includes firm purchases of access capital equipment.

2.2 Existing literature

We now discuss the existing literature in the light of equation (9).

First, much of the work specific to the contribution of communications uses cross-country data following the method of Röller and Waverman (2001). That paper argues that expansion of the telecommunications infrastructure generates excess returns to telecoms capital (which may be due to network effects, although they do not estimate network effects directly) and contributes to production in ways (e.g. reduced transaction costs, collaboration/co-operation benefits, process innovations etc.), which might raise TFP if not priced into an input's reward. They seek to address potential simultaneity bias and reverse causation by endogenising CT investment, and present evidence of a causal relationship between fixed line telephone penetration and economic growth. Koutroumpis (2009) and Gruber and Koutroumpis (2011) follow a similar method, finding a link between broadband penetration and GDP growth e.g. Gruber and Koutroumpis (2011) find that, in high income countries, mobile telecommunications infrastructure contributes 0.2% pa to growth in GDP, compared to 0.11% pa in low income countries and Koutroumpis (2009) finds that a 1% increase in the penetration rate raises growth in GDP by 0.025% pa, 2002-07.

Equation (9) suggests one should find a link between TFP growth and various measures of telecoms presence, but the interpretation of that link varies. It is likely for example that (changes in) fixed/mobile/broadband penetration are correlated with dk^{ACC}, $d\mu$ and dk^{NET} but without knowing which effect is which the interpretation in terms of utilisation and/or network effects is not clear and one cannot read off a value for γ.

Second, there is of course a large literature on the relation between ICT and growth in labour and total factor productivity, where spillovers might appear for a number of reasons. First, as we argue, due to telecommunications network effects, the C in ICT. Acharya and Basu (2011) use industry data to explore whether there is evidence of productive externalities from ICT capital but find a negative correlation between telecoms capital deepening and output growth. Stiroh (2002) finds that the late 1990s acceleration in US (manufacturing) TFP was *not* correlated with growth in ICT capital outside the ICT-producing industries, implying that the contribution of ICT is estimated as fully accounted for in the contribution of ICT capital deepening, which accounts for capital-embodied technical change provided one applies quality-adjusted ICT deflators. Specifically for CT equipment, he finds a consistent negative correlation with growth in TFP, which is argued could reflect adjustment costs and/or mismeasurement. Van Reenen et al. (2010) find no evidence of ICT (productivity) spillovers once they control for industry and region characteristics.

Stiroh (2005) provides a review of ICT-output elasticities across an array of studies using a range of differing data, methods and specifications. He finds that studies that use aggregate data (as opposed to say, firm-level data) and/or "later" data (in terms of the time period considered), tend to report larger ICT elasticities. Conversely, studies that: use gross output (as opposed to value-added); incorporate fixed effects; or incorporate first-differences rather than work with levels; report lower ICT elasticities. Using US industry data for the private sector, he provides evidence consistent with ICT spillovers, but emphasises the importance of specification for estimated elasticities and their precision. Again his results are however not supportive of separately indentifiable spillovers from telecommunications capital.

A second reason is the use of ICT (and in particular, the internet) to facilitate innovation and improve the efficiency of the research process as described in literature from the OECD (2000) and Mokyr (2014).[13]

A third reason concerns the nature of ICT as a general purpose technology (GPT). Simply defined, GPTs are (initially ground-breaking) technologies, embodied in capital, that diffuse throughout the economy and become ubiquitous due to their wide range of uses and general purpose nature. Features of GPTs include their pervasiveness, inherent potential for technological improvement, and complementarities with other innovative technologies ((Edquist and Henrekson, 2016);(Bresnahan and Trajtenberg, 1995)), with other examples including steam and electricity. David (1990) emphasises parallels between ICT and the electric dynamo, noting how each give rise to "network externality effects" as well as documenting the lag between their introduction and their effect on measured aggregate productivity.[14] The reason for such a lag is to allow for diffusion of the technology (it took over two decades for electrification to reach a diffusion level of 50% (David, 1990)) and for users to learn or understand the ways in which it can be used.

A related fourth reason is that such a lag reflects the time taken to build capabilities within the organisation by investing in complementary intangible assets. In a series of papers, Brynjolfsson and Hitt (e.g. (2003)) use microdata to estimate the contribution of ICT to productivity growth, including any long-run effects which they consider to represent the returns to complementary intangible investments. They find that the ICT contribution grows over time, with longer-run contributions (five to seven years) as much as five times greater than the short-run contribution, where the latter is in line with the ICT cost share. Corrado et al. (2013) present evidence of externalities from intangibles, and show that the estimated ICT-output elasticity is reduced once intangibles are accounted for, suggesting complementarities. Chen et al. (2016) present a survey on the productivity impact of ICT and intangibles and show that the contribution of intangibles is greater in more ICT-intensive industries.Vecchi et al. (2013) present evidence for a negative contemporaneous correlation between industry ICT input and productivity, but find that this turns positive five years after the initial investment, which is consistent with the hypothesis of lower measured output around the time of investment (as firms divert resources to the accumulation of complementary intangible capital), with stronger productivity growth coming with some lag as firms benefit from their (and potentially others') investments in ICT and complementary intangibles.

Of other papers that study the correlation between ICT and TFP growth: Gehringer et al. (2015) present a positive correlation between ICT and TFP, but do not consider CT capital separately; O' Mahony and Vecchi (2016) present evidence of excess returns to ICT using data for US (non-farm) industries; based on Dutch microdata, results in Van Leeuwen et al. (2003) are supportive of excess returns to ICT capital deepening, over and above the ICT cost share, due to spillovers; and Venturini (2015) finds evidence of ICT externalities distinct from those due to activity in R&D, but where the former enable the latter.

To account for potentially important omitted variables, we also look for evidence consistent with spillovers from the conduct of public and private R&D. There is an extensive literature on spillovers from R&D with much evidence to suggest that social returns do indeed exceed private returns. Surveyscan be found in Hall et al. (2009) and Griliches (1973). As in Griliches (1992), Schmookler (1966) and Scherer (1982), we seek evidence of a correlation between growth in TFP and growth in the stock of R&D, although we work at

[13] Using UK industry data on upstream R&D activity and downstream outputs and inputs, Corrado et al. (2011) estimate strong TFP in the R&D process and show that this implies a rapidly falling investment price index for UK R&D.

[14] In the case of ICT this is well-documented and is usually highlighted with reference to the famous quip attributed to Solow, that we "see computers everywhere except in the productivity statistics" (New York Times Book Review, July 12, 1987).

the whole economy (country) level as opposed to the industry- or firm-level, and we look for evidence of effects within, rather than between, countries. Mc Morrow and Röger (2009) also review the literature and summarise R&D-output elasticities that lie in the range of 0.1 to 0.2.[15] Using data for the UK, Haskel and Wallis (2013) find evidence of a large social rate of return to the public science budget, and Goodridge et al. (2016b) present evidence of intra- and inter-industry spillovers from R&D, as well as other forms of knowledge capital such as training and organisational capital.

3 Data and estimation of the model

3.1 Data

3.1.1 Inputs, outputs and TFP

Before presenting our results, we first set out some details on our underlying dataset. Full details on the construction of the dataset are provided in Goodridge et al. (2016a).

For each capital asset, we have nominal capital investment in asset type a and a price index for investment goods of each type, where each are uncertain due to difficulties in unbundling different elements of ICT investment and an absence of quality-adjustment. Thus we build capital stocks of type a by a perpetual inventory model (PIM) so that for K_a we have:

$$K_{a,t} = \frac{P^*_{Ia} I_a}{P_{Ia}} + (1 - \delta^{Ka}) K_{a,t-1} \tag{10}$$

Where δ^{Ka} is an asset-specific depreciation rate and note that P^*_I, the true price of investment in asset a, may differ from the measured price of investment, P_I. Our asset types are: buildings, IT equipment, CT equipment, other plant & machinery, vehicles, software, R&D, and mineral exploration and artistic originals (investment in these latter two assets combined). Asset-specific rental costs are estimated by applying the user-cost relation between P_I and P_K:

$$P_{Ka} = P_{Ia}(\rho + \delta^{Ka} - (\Delta P_{Ia}/P_{Ia})) \tag{11}$$

Where ρ is an economy-wide nominal net rate of return equalised across all assets via competitive arbitrage.[16] User costs sum to economy-wide gross operating surplus and income shares for each asset sum to the total capital income share, which in turn is one minus the labour income share.

P_{Ka} are the price of capital services from asset type a. Capital services are translog aggregations over heterogeneous capital types a, where shares are of total capital payments for each asset type, averaged over the current and previous period in order to form a superlative index. [17]

$$\Delta lnK = \sum s_K^{Ka} \Delta lnK_{a,t} \tag{12}$$

[15] To preview our results, the upper range for our estimates of the output elasticity of R&D lie at the lower end of this range.

[16] Due to incomplete data across countries, we do not apply tax adjustment factors in the estimation of user costs.

[17] Estimation of labour services is perfectly analagous. Labour is in natural units, hours. P_{Lb} are the prices for labour services from labour type b. Labour services are translog aggregations over heterogeneous labour types b: $\Delta lnL = \sum s_L^{Lb} \Delta lnH_{b,t}$. Where $H_b$are the annual person-hours worked by type b workers and shares are of total labour payments for each type, averaged over the current and previous period: $s_L^{Lb} \equiv \frac{1}{2}\left(\left(\frac{P_{Lb}L_b}{P_L L}\right)_t + \left(\frac{P_{Lb}L_b}{P_L L}\right)_{t-1}\right)$. Thus labour services are adjusted for composition of the workforce.

$$s_K^{Ka} \equiv \frac{1}{2}\left(\left(\frac{P_{Ka}K_a}{P_K K}\right)_t + \left(\frac{P_{Ka}K_a}{P_K K}\right)_{t-1}\right) \quad (13)$$

For each factor input, s is an income share estimated as an average over the two periods (we omit the usual overbar just to ease notation):[18]

$$s_Q^K \equiv \frac{1}{2}\left(\left(\frac{P_K K}{P_Q Q}\right)_t + \left(\frac{P_K K}{P_Q Q}\right)_{t-1}\right) \quad (14)$$

Finally, using data on factor inputs and payments, we decompose growth in value-added (Q)[19] into contributions from labour, capital, and the residual, total factor productivity (TFP):

$$\Delta \ln Q_t \equiv s_Q^L \Delta \ln L_t + s_Q^K \Delta \ln K_t + \Delta \ln TFP_t \quad (15)$$

Using these data we calculate TFP growth as :

$$\Delta lnTFP_{c,t} = \Delta lnQ_{c,t} - \left(s_{c,t}^L \Delta lnL_{c,t} + s_{c,t}^{K^{CT}} \Delta lnK^{CT}{}_{c,t} + s_{c,t}^{K^{IT}} \Delta lnK^{IT}{}_{c,t} + s_{c,t}^{K^{NON-ICT}} \Delta lnK_{c,t}^{NON-ICT} + s_{c,t}^R \Delta lnR_{c,t}\right) \quad (16)$$

where the subscript c is country, Q is value-added, L are labour services (incorporating labour composition), $K^{CT}$are capital services from communications equipment, $K^{IT}$are capital services from IT hardware equipment and $K^{\text{NON-ICT}}$are capital services from other tangible, but non-ICT, equipment. R are capital services from measured National Accounts knowledge capital (software, R&D, mineral exploration and artistic orginals).

3.1.2 Countries in data

We use the dataset constructed in Goodridge et al. (2016a), which includes data on output, factor inputs and productivity for fourteen OECD economies: the US, and thirteen European countries. Those latter countries are: Austria (AUT); Belgium (BEL); Denmark (DNK); Spain (ESP); Finland (FIN); France (FRA); Germany (GER); Ireland (IRL); Italy (ITA); the Netherlands (NLD); Portugal (PRT); Sweden (SWE); and the United Kingdom (UK).

Our dataset includes estimates of real and nominal gross value-added (GVA), gross fixed capital formation (GFCF), GFCF price indices, capital services, user costs and factor shares, labour services and labour composition, hours worked and TFP growth for each of these fourteen OECD countries. Our earliest TFP estimates begin in 1990 for some countries (AUT, ESP, FIN, FRA, ITA, NLD, UK, US), 1995 for GER, 1997 for SWE, and 1999 for remaining countries (BEL, DNK, IRL, PRT). Data for all countries end in 2013.

3.1.3 Capital input deflators

Estimates of capital services for each ICT asset (IT hardware, CT equipment and software) are constructed using OECD harmonised deflators from Schreyer and Colecchia (2002). These price indices are harmonised

[18] Similarly, for labour: $s_Q^L \equiv \frac{1}{2}\left(\left(\frac{P_L L}{P_Q Q}\right)_t + \left(\frac{P_L L}{P_Q Q}\right)_{t-1}\right)$

[19] Since Q is estimated using national ICT price indices, we re-estimate Q using investment shares in value-added and the harmonised constant-quality ICT price indices from the OECD.

with constant-quality hedonic ICT price indices for the US, where the method to harmonise is to set the ratio of ICT to non-ICT prices in other countries equal to the ratio in the US. Or in terms of the log change, the log change in the ICT price index for the chosen country is estimated as the log change in the US price index, less the log change in the US non-ICT price index, plus the log change in the non-ICT price index in the chosen country, as set out in (17).

$$\Delta lnPi_{c,t}^{ICT} = \Delta lnPi_{US,t}^{ICT} - \Delta lnPi_{US,t}^{NON-ICT} + \Delta lnPi_{c,t}^{NON-ICT} \quad (17)$$

Use of constant-quality prices means that we are less likely to underestimate the contribution of ICT assets by better capturing increases in the volume of ICT investment and capital services, due to improvements in the power or efficiency of the underlying technology. Thus we can be more confident that any evidence of an excess return to ICT equipment is not a result of the underestimation of capital services. As a result we reduce the possibility of ascribing 'pecuniary' spillovers to pure spillovers, due to mismeasurement of prices. We also produce alternative estimates of ICT capital services using the deflators produced by national statistical institutes (NSIs), and test robustness to using these measures. Capital services estimates for all other assets are estimated using NSI deflators.

It might be argued that use of the US price indices, either in original or adjusted/harmonised form, for other countries is not appropriate if those countries face different prices or if the composition of telecommunications (or other ICT) investment differs across countries. However, first, as noted in Corrado (2011b), the pace, pattern and profile of price changes in CT equipment are remarkably similar across a diverse range of technologies, products and varieties. Second, these are internationally traded products and so we would expect them to be priced competitively across countries. And third, the use of US ICT price indices has become accepted research practice and in some cases these indices are also applied by NSIs in national measurement.[20]

Our dataset was primarily built using country-level total economy data downloaded from OECD.Stat, which contains national accounts data submitted to the OECD by NSIs of member countries. Where data were incomplete or missing, the data were supplemented with data from other sources, with some extrapolation or imputation where necessary. For details, please see Appendix B.

On the primary subject of this paper, communications equipment, we note that measurement issues may exist in cases where different aspects of ICT are bundled in the same purchase. In the case of hardware, we note that the convention is that where software is bundled with hardware, and the values cannot be separated, then the investment transaction is recorded in hardware. We assume that the same applies to communications equipment, and that where software is bundled with CT and the values cannot be separated, then the transaction is recorded in CT. Where CT is bundled with IT, we assume the transaction is recorded under IT hardware. However, we note the potential for practice to vary by country, with different countries potentially applying different methods and varying degrees of effort in unbundling various aspects of ICT investment.

3.1.4 Public R&D and intangible capital services

As well as the data from our growth-accounting exercise, we also incorporate into our model data on public R&D, performed by the Government and Higher Education sectors as recorded in GERD and published by

[20] Official UK estimates of capital services produced by the ONS make use of (exchange rate or PPP adjusted versions of) US price indices for IT hardware and pre-packaged software.

the OECD. Our (private) R&D capital services data exclude public R&D. We therefore account for it in our estimation by simply including the ratio of public R&D ($P^N N^{PUB}$) to GDP ($P^Q Q$). The resulting coefficient is an estimate of the total social rate of return to public R&D.[21]

In our growth decomposition we account for all intangible capital types already capitalised in the national accounts with the exception of public R&D, therefore including: (private) R&D, mineral exploration, artistic originals and software (and databases).[22]

3.2 The transition to econometric work

We experiment with different specifications, but using country-year panel data, the basic equation we estimate is:

$$\Delta_M lnTFP_{c,t} = \alpha + \Sigma d^X \Delta_M lnX_{c,t-k} + \lambda_c + \lambda_t + u_{c,t} \tag{18}$$

Where $\Delta_M$refers to the length of the difference taken, between one and five years, and λ terms control for time and, in some cases, country fixed effects (in general, for reasons explained in a section below, we use random effects, but we present alternative results using fixed effects in the Appendix). X are various capital services variables, notably K^{CT}. Note that since CT, IT and (private) R&D are already accounted for in the estimation of TFP, any effect here is over and above the private returns estimated in our growth decomposition.

Regarding the practical implementation of this equation, the following points are worth noting.

3.2.1 Specification

First, as we are seeking evidence of externalities derived from capital after that capital has been utilised in production, we assume a lag structure to spillover diffusion as indicated by the subscript (t-k). $\Delta lnX_{c,t-k}$ are growth in capital services from telecommunications capital, IT hardware, and R&D, lagged k periods. Since we have little a priori evidence on the correct lag structure we experiment with different values although we note that Basu et al. (2003) suggest long lags of around five (to fifteen) years in the context of total ICT equipment. In their work with microdata, Brynjolfsson and Hitt (2003) suggest lags of five to seven years.

Second, we include capital services from IT hardware equipment on the grounds that: a) there may be separately idenitifiable network effects and externalities that derive from the use of IT; or alternatively b) that

[21] The reason we exclude public R&D from our measure of (private) R&D capital services is that it is typically assumed that, due to its more basic nature, public R&D either does not depreciate or at least depreciates more slowly than privately performed R&D. Thus R&D capital services would be incorrectly measured due to the application of the same geometric depreciation rate (20%) to both private and public R&D. Therefore, in our estimation of R&D capital services and TFP, we only incorporate private R&D, with a 20% geometric depreciation rate. This helps in the interpretation of our coefficients. Our estimated econometric coefficient on private R&D is an excess elasticity. Public R&D was not accounted for in the estimation of TFP so the estimated public R&D coefficient is an estimate of the gross social rate of return to public R&D. We note that conceptually this procedure is consistent with national accounting data and methods. According to national accounting convention, the cost of public (i.e. government) capital consists of capital consumed (i.e. depreciation) but does not incorporate a rate of return (i.e. profit rate) since it is assumed that public assets generate no net operating surplus (see for example Jorgenson and Schreyer (2012)). However, in our estimation of the user costs of capital (for R&D and all other assets), we do incorporate the net rate of return to capital, as shown below in equation (11). Thus our modified treatment of R&D is consistent with national accounting practice, although we lack the data to apply any adjustment to the other assets included in our growth decompositions. Although not reported, in robustness checks we have re-estimated our coefficients using measures of R&D capital services and TFP calculated with public R&D included, and the conclusions are the same.

[22] In separate work for the UK, Goodridge and Haskel (2015;2015b;2015a;2016) estimate UK market sector investment in the building/transformation and analysis of data, and estimate that around three-quarters of such investments are already captured in the official measurement of software in the UK.

the unbundling of ICT investment as undertaken by national statistical agencies means that, in practice, some part of investment in CT equipment remains measured within IT equipment.[23] To reduce omitted variable bias, we also account for both private and public R&D, but using separate terms for (private) R&D capital services and the public R&D/GDP ratio.

Third, theory suggests we should include share-weighted network and access capital growth and utilisation. We do not have measures of the correct shares, as above, since we do not have measures of consumer investment in access capital, and utilisation measures are not clear. Thus we simply enter ΔlnK as a proxy for all these measures and look for a correlation: later we shall see under which assumptions we may recover an estimate of γ.

Fourth, some research conjectures that ICT capital itself generates externalities which diffuse to other firms/industries, but other suggests that in order to reap productivity advantages, investment in ICT requires complementary investments in intangible (or knowledge) capital. Some intangibles are included in national accounts but in robustness checks we also include contemporaneous and lagged measures of other intangible capital services.[24]

3.2.2 Econometric considerations

Turning to some more econometric considerations, contemporaneous correlations between TFP growth and changes in capital input could be due to unmeasured utilisation, or reverse causation and impose instant spillover transmission. We experiment with some IV approaches below, but in most specifications we use lagged independent variables.

On measurement error,[25] we attempt to minimise it in two ways. First, in our estimation of ICT capital services and TFP, we apply consistent, harmonised estimates of ICT price change across countries (Schreyer and Colecchia, 2002), consistent with hedonic price indices produced by the BEA, the global leader in developing constant-quality price indices for ICT equipment. Thus, any reported correlation is less likely to be due to under-measurement of ICT capital contributions due to a failure to apply constant-quality price indices in estimating capital services and TFP.

Second, annual estimates of TFP growth based on first differences incorporate a significant degree of noise. Therefore we also experiment with longer differences, which hopefully removes noise from the data and helps uncover what are likely to be long run economic relations (for example, it is unlikely that TFP growth responds to one-off annual increases or decreases in the public science budget of say 5%, rather, it depends on the long run level).

We shall try to account for measurement error in our explanatory variable(s) following the method set out in Griliches and Hausman (1986), and used in, for example, Goolsbee (2000) as follows. Dropping time

[23] The extent to which this is the case likely varies across countries, but from our discussions with the UK Office for National Statistics we know that they are reviewing their data and methods for the disaggregation of investment in plant and machinery including ICT equipment.

[24] The data are from the SPINTAN project (http://www.spintan.net/) and consist of growth in capital services for innovative property excluding R&D and economic competencies, each defined as in Corrado et al. (2005) (CHS). We also include growth in capital services from computerised information (software and databases) as measured in the national accounts, in case that ICT/intangible asset also generates some form of excess return or network effect.

[25] Our explanatory variable predominantly of interest is growth in capital services from telecommunications equipment, derived from estimates of the level of the telecoms capital stock. However, the true level of the stock is unknown without some assumption on its initial value in the starting year of the data, which is also unknown. There is also uncertainty around the true price of CT (and other ICT) capital, although we seek to minimise this in our use of harmonised constant-quality deflators, and the extent to which telecoms investment is fully 'unbundled' from other ICT investment in its measurement. Thus we can be confident that there is at least some degree of measurement error in our explanatory variable.

and country subscripts for clarity of notation, let us denote correctly-measured variables by a *. Suppose the true model, in levels, is that Y depends upon two variables X* and Z:

$$Y = \beta X * + \gamma Z + v \tag{19}$$

The regression anatomy formula (Angrist et al., 2009) suggests $\hat{\beta}$ is given by:

$$\widehat{\beta} = \frac{Cov(Y, \tilde{X}*)}{Var\tilde{X}*} \tag{20}$$

where $\tilde{X*}$ is the residual from a regression of X* on Z

$$X* = \pi_O + \pi_1 Z \tag{21}$$

Suppose further, as is conventional, that we observe only X which is measured with error:

$$X = X * + m \tag{22}$$

which also implies that:

$$\tilde{X} = \tilde{X} * + m \tag{23}$$

Let us assume that only X is measured with error and that Z is uncorrelated with m. And suppose finally that the regression uses the measured variable:

$$Y = \beta X + \gamma Z + u \tag{24}$$

Using (20), the estimator of β is:

$$\begin{aligned}
\widehat{\beta} &= \frac{Cov(Y, \tilde{X})}{Var\tilde{X}} && (25)\\
&= \frac{Cov(\beta X^* + \gamma Z + v, \tilde{X} * + m)}{Var\tilde{X}} && (26)\\
&= \beta \frac{Var(\tilde{X}*)}{Var\tilde{X} * + Var(m)} = \beta\tilde{\lambda} && (27)
\end{aligned}$$

where $\tilde{\lambda}$ is the reliability ratio (not of X but) of $\tilde{X}$ and this shows that, as is well-known, β is biased down (since $0 < \tilde{\lambda} < 1$). So (27) simply restates the familiar measurement error bias equation in the case of more than one regressor. Suppose now that all the above holds and we run the equation in first-differences. Then the bias to β is:

$$\begin{aligned}
\widehat{\beta_{FD}} &= \beta_{FD} \frac{Var(\Delta\tilde{X}^*)}{Var(\Delta\tilde{X}*) + Var(\Delta m)} = \beta_{FD}\tilde{\lambda_\Delta} && (28)\\
&= \beta_{FD} \left(\frac{2\sigma^2_{\tilde{X}*}(1-\rho)}{2\sigma^2_{\tilde{X}*}(1-\rho) + 2\sigma^2_m(1-r)} \right)
\end{aligned}$$

where r is the serial correlation in the measurement error and ρ the serial correlation in the true $\tilde{X}*$.

Note that, as usual, differencing reduces bias if (1-r)/(1-ρ) is small, which is the case if r is large (near 1) and ρ is small (near zero). In practice however, we know little about these correlations. In the one variable case, X is capital, then ρ is the serial correlation coefficient in true lnK. From the PIM, serial correlation in the true K is $(1-\delta)$ but serial correlation in lnK is not immediately clear. What then is r, the serial correlation in the error in measured lnX? If such error comes from an erroneous initial capital stock, it is also $(1-\delta)$ (in K at least). In addition, if P^I is systematically wrong then $P^I I$ is likewise in error which also carries over to K. Thus it is quite possible that $r > \rho$ or that even $r = \rho$. However, we need not the serial correlation in K but the serial correlation in $ln\tilde{K}$, that is, the serial correlation in the regression of true lnK on true other capital stocks. This serial correlation is likely to be high, since we are regressing a capital stock on other capital stocks, all of which are likely integrated of order zero (I(0)).

In the absence of other data, let us assume that $r = \rho$ in which case we can use the results of Griliches and Hausman (1986) who observe that information on σ_m^2 can be obtained if one notes that estimates of β can be obtained using differences of length M as follows:

$$\hat{\beta_M} = \beta\left(1 - \frac{2\sigma_m^2}{Var(\Delta_M ln\tilde{X})}\right) \tag{29}$$

Using (29) with differences of length M and N, divides and rearranges, giving an estimate of the fraction of the $\tilde{X}$ variance that is measurement error, as shown below:

$$\frac{\sigma_m^2}{Var(\Delta_M ln\tilde{X})} = \frac{Var(\Delta_M ln\tilde{X})}{Var(\Delta_N ln\tilde{X})} \frac{\frac{\widehat{\beta}_M}{\widehat{\beta}_N} - 1}{2\frac{\widehat{\beta} a_M Var(\Delta_M ln\tilde{X})}{\widehat{\beta}_N Var(\Delta_N ln\tilde{X})} - 1} \tag{30}$$

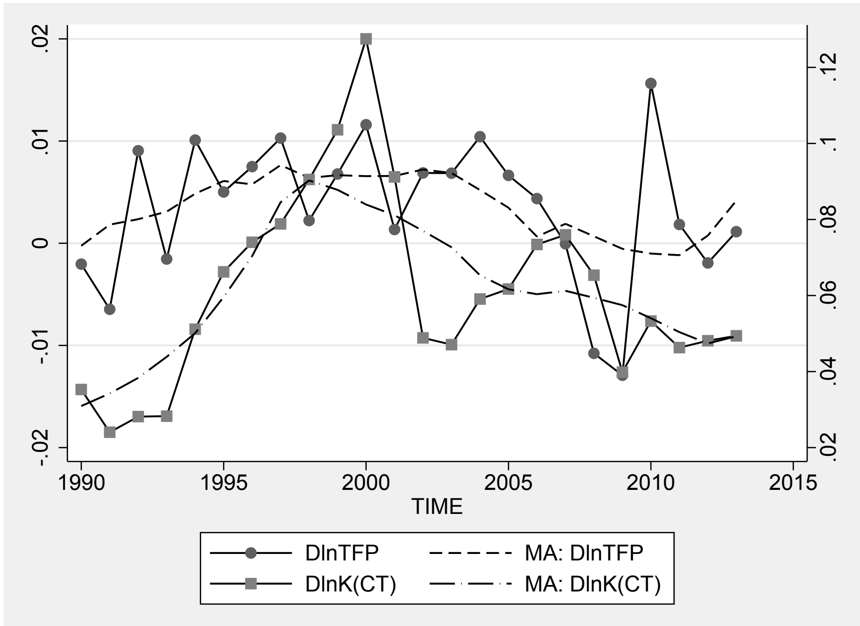
With an estimate of this fraction, we can substitute back into (28) and get an estimate of the downward bias to β. We present our results of this procedure in section 5.2 below.

4 Correlations and regression results

4.1 Raw correlations

Before presenting our results, we first display some charts for the correlations we are seeking to estimate. Figure 1 presents data on growth in TFP and growth in telecoms capital services for the aggregate of the fourteen countries in our dataset, each constructed as share-weighted aggregates. The blue connected line is annual TFP growth (left-hand y-axis) and the green connected line is annual growth in telecoms capital services (right-hand axis). To better display the trend in each, the red and orange lines are respectively moving averages of TFP growth and CT capital services growth, each estimated using the current period, three lead periods and three lagged periods, all equally weighted. The first thing to note is the dramatic growth, and acceleration in growth, of telecoms capital services in the 1990s, particularly the late 1990s. We interpret this period as one of network build-out, with much investment being in creating network infrastructure by the telecommunications industry itself. Annual TFP growth is noisy but focusing on the trend line we see that TFP growth also accelerated in the 1990s before starting to decelerate in the early 2000s, by which point, growth in telecoms capital services had also slowed. Toward the end of the series', since the recession, telecoms capital services growth has again accelerated, and there has also been some recovery in growth of TFP. These aggregates are suggestive of a correlation between growth in telecoms

Figure 1: $\Delta\ln\mathrm{TFP}_{c,t}$ vs $\Delta\ln\mathrm{K}_{c,t}{}^{\mathrm{CT}}$, 14-country aggregate (US & EU-13)



Note to figure: Connected line (circles) is annual TFP growth for the aggregate of the fourteen countries in our dataset (left-hand axis). Other connected line (squares) is annual growth in CT capital services for the same aggregate (right-hand axis). Dashed and dotted lines display the trend for each respectively, constructed as a moving average using 3 lagged values, 3 lead values, and the current period, all equally weighted.

capital services and growth in TFP, and suggest that there is some lag in that correlation.

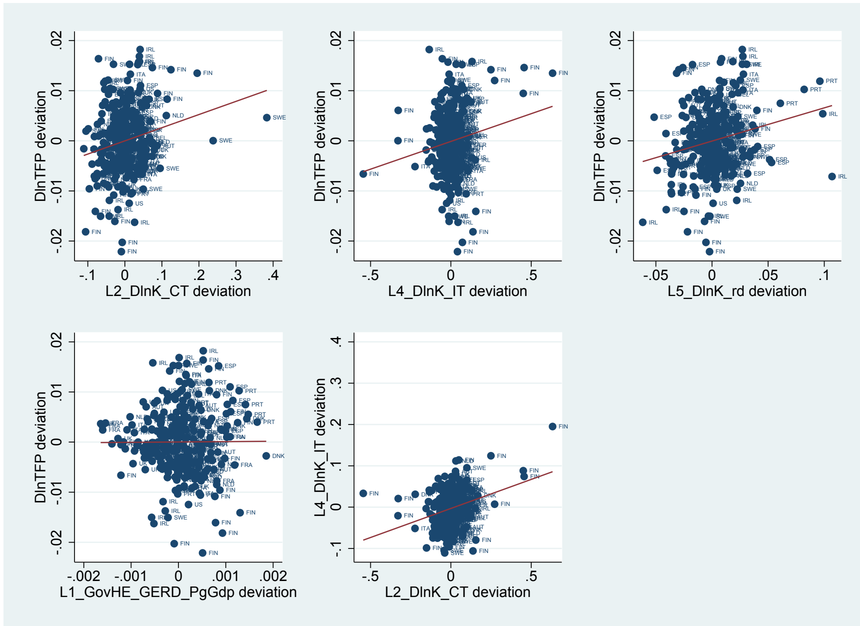
In our estimation we work at the country-level. To study the correlations, Figure 2 plots growth in our explanatory variables against growth in TFP. In producing these charts we experimented with different lags on our explanatory variables. We introduce lags for two reasons: first, intuitively, it seems likely that the diffusuion of spillovers takes some time, although we might expect benefits from participation in a telecoms network effects to materialise quicker than say, those from a new scientific discovery; and second, introducing lags to our explanatory variable helps mitigate issues stemming from endogeneity.

The first chart, top left, plots CT capital services lagged twice (t-2) versus TFP . We find a correlation using zero (t), one (t-1), two (t-2) or three (t-3) lags, but the correlation is strongest with either one or two lags. All data points are in terms of the deviation from the time and country mean. The correlations therefore show that following periods of above average growth in CT capital services in a particular country, TFP growth was higher than average in subsequent periods. The points to the left and right of each chart are primarily observations for Finland and Sweden.

In the second chart, top middle, we present a similar chart suggesting a positive correlation but this time using capital services from IT hardware with four lags. Similar charts using different lag structures suggested a stronger correlation using either three (t-3) or four (t-4) lags. In the case of IT hardware, evidence from the literature is also suggestive of any spillovers operating with a longer lag. Data points for Finland are again shown to lie in the top right and bottom left quadrants of the charts in the case of both CT and IT.

In the third chart, top right, we present the correlation with private R&D capital services. In the case of private R&D, the correlation appears strongest when working with either four or five lags. Here we present

Figure 2: $\Delta \ln TFP_{c,t}$ vs $\Delta \ln X_{c,t-k}$, all in deviations from time and country mean



Note to figure: Each point is a country. Estimates for growth in TFP and capital services all in deviations from the time and country mean. Top left is CT capital services, t-2. Top middle is IT capital services, t-4. Top right is(private) R&D capital services, t-5. Bottom left is the public R&D:GDP ratio, t-1. Bottom middle is CT capital services (t-2) plotted against IT capital services (t-4). Growth rates calculated as changes in the natural log.

the fifth lag. In the top right and bottom left quadrants we again observe data points for Finland, as well as Ireland and Portugal.

In the fourth chart, bottom left, we present the correlation between growth in TFP and the flow of public R&D in GDP, lagged one period. The line of best fit is flat and the correlation turns negative as the length of lag is increased.

Finally, bottom right, to preview our results we present the correlation between CT and IT capital services and note that they are quite collinear.

4.2 Results

The key lesson learned from research into the contribution of ICT equipment to growth was that accurate estimation required use of hedonic or quality-adjusted deflators (see for example Triplett (2004)), so that changes in ICT prices reflect improvements in computing power and other characteristics, as well as falls in listed prices, and thus measures of real ICT investment and capital services reflect changes in the real quantity of capital available for production.

In this paper, all of our primary results are derived using harmonised quality-adjusted deflators for ICT assets produced by the OECD (Schreyer and Colecchia, 2002). As a result, we can be more confident that any statistically or economically significant correlation that we uncover is not the result of underestimation of ICT capital services and contributions due to a failure to account for improvements in ICT characteristics. As a robustness check, we also apply the (implied) deflators submitted to the OECD by NSIs to check as to what extent this affects our results.

Table 1 presents our first set of results, using differences in country-year panel data for fourteen countries over the years 1990 to 2013. Our basic equation for estimation is:

$$\Delta_M lnTFP_{c,t} = \alpha + \Sigma d^X \Delta_M lnX_{c,t-k} + d^{PUB} \frac{P^N N^{PUB}_{c,t-k}}{P^Q Q_{c,t-k}} + \lambda_t + u_{c,t} \tag{31}$$

Where X are capital services from CT, IT or private R&D. All regressions are estimated using random effects.

In constructing our preferred specification we first conducted the Breusch and Pagan LM test for random effects, which confirmed that we ought to estimate with random effects, as opposed to a pooled OLS regression. We then conducted a Hausman test, the results of which showed that we ought to estimate with fixed (country) effects.

However, when studying the standard deviation of variables within and between countries, we found that in general, in the case of our capital services variables (CT, IT and private R&D), there is variation in both the time-series and the cross-section. In the case of CT, more of the variation is within the time-series ($\sigma = 0.056$) compared to that between countries ($\sigma = 0.037$). For IT hardware, the majority of the variation is within the time-series, $\sigma = 0.108$, compared to $\sigma = 0.026$ between countries. For private R&D, the standard deviations within and between countries are $\sigma = 0.024$ within countries and $\sigma = 0.034$ between countries. Thus, in the case of private R&D capital services, the majority of variation is between countries, in the cross-section. The same is true, but to a much greater extent, for the public R&D/GDP ratio. For this variable, we find that within countries, $\sigma = 0.0008$, compared to $\sigma = 0.0018$ between countries, meaning there is very little variation in the time-series, but much more variation in the cross-section. Thus we conjecture that incorporation of country fixed effects means that we are absorbing the cross-sectional variation between countries in the dummies, leaving little room for explanatory variables that mainly differ in the cross-section. Therefore in the table below we present results that use random effects, but we present alternative results in our robustness checks and the Appendix based on fixed effects. The main differences are that: a) when using random effects, we find a more consistent correlation between TFP growth and the flow of public R&D; and b), the coefficients on our capital services variables tend to be slightly larger when we include fixed effects.

Our results are shown in columns 1 to 10 of Table 1. The dependent variable in each regression is growth in TFP and explanatory variables are lagged[26] for two reasons. First, we consider that instant spillover transmission is not realistic, and second, due to issues of endogenity and simultaneity when using contemporaneous terms.[27] All regressions include year dummies and are estimated with robust standard errors. Columns 1 to 9 are estimated using random effects.

Above we have noted potential measurement issues around the unbundling or disaggregation of GFCF in ICT equipment into distinct components for IT hardware and CT equipment. Our hypothesis is that network effects derive from CT equipment. If however the disaggregation is incomplete or imperfect then there may also be a correlation between growth in TFP and growth in capital services from ICT equipment, or even IT hardware. In Table 1 we present a series of regressions using these three independent variables (ICT equipment, IT hardware equipment and CT equipment), starting with ICT equipment and followed by its elements. According to the classical measurement error scenario, such error ought to mean that a correlation will be observed but that there will be downward bias to the estimated coefficient.

Thus, in column 1, for our explanatory variables we include lagged terms for growth in ICT equipment capital services ($\Delta \ln K_{t-3}{}^{ICT}$), growth in private R&D capital services ($\Delta \ln K_{t-5}{}^{R\&D}$) and the public R&D:GDP ratio ($\frac{P^N N_t^{PUB}}{P^Q Q_t}$). ICT equipment capital services are estimated using GFCF price indices recorded in each country's national accounts. We find that it enters with a strongly significant coefficient implying an (excess)[28] output elasticity of 3.3%. Growth in private R&D capital services is lagged five times, is also strongly statistically significant, and has a coefficient implying an output elasticity of over 4%. The coefficient on public R&D is positive and can be read directly as a social rate of return, suggesting a surely over-estimated gross social rate of return of 214%.

In column 2 we run the same regression but this time with changes in TFP and ICT capital services estimated using OECD harmonised ICT deflators, with little substantive impact on our results.

In the remaining columns we seek to test: a) whether the observed ICT equipment correlation is also observed for one or both of its components; and b) whether results based on longer differences are supportive of our measurement error hypothesis. We therefore estimate a series of regressions based on first and longer (four year) differences. To isolate effects due to changes in specification as opposed to the sample, all regressions after column 2 (except column 10) are estimated on the same 244 observations. Column 2 is based on first differences and column 3 uses long differences. We find that moving to longer differences raises our estimated elasticities, which is consistent with measurement error in the explanatory variable. That on ICT equipment is raised from 3.2% to 4.1% and remains strongly statistically, whilst that on private R&D is raised to 6.1%, although the latter is less precisely estimated and only significant at the 10% level. The coefficient on public R&D is also less precisely estimated and with a reduced, but still very large, coefficient.

From column 4 onwards, we disaggregate capital services from ICT equipment into those from CT equipment and IT hardware, and alternate between short and long differences. We find that estimation is

[26] Except for column 10 which is the second stage of an IV regression using contemporaneous terms.

[27] Although not presented here, we ran a series of regressions to determine which lag structure was most effective. In general, we found that ICT capital services are statistically significant with one, two, three, or four lags, but the effect was strongest with three or four lags. With ICT capital services disaggregated into IT and CT capital services, our findings were similar, but statistical significance tended to be stronger with a slightly shorter lag for CT (two lags work best) and a slightly longer lags for IT (four lags work best). For private R&D, results were stronger with a longer lag of four or five periods. For public R&D, due to the lack of time-series variation within countries, we found that our results were largely invariant to the number of lags taken.

[28] We describe the elasticity as an excess elasticity as it is the effect on output growth over and the above the elasticity uncovered via growth-accounting, as estimated by the ICT equipment factor share in total income.

Table 1: Regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ICT (NAs)	ICT (OECD HDs)	ICT	IT & CT	IT & CT	CT	CT	IT	IT	CT
	Short (M=1)	Short (M=1)	Long (M=4)	Short (M=1)	Long (M=4)	Short (M=1)	Long (M=4)	Short (M=1)	Long (M=4)	IV (Short)
VARIABLES	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	ΔlnTFP
$\Delta_M \ln K^{ICT}_{t-3}$	0.033***	0.032***	0.041***							
	(3.28)	(3.27)	(3.11)							
$\Delta \ln K^{CT}_{t}$										0.073***
										(2.77)
$\Delta_M \ln K^{CT}_{t-2}$				0.033*	0.050	0.040**	0.060**			
				(1.67)	(1.49)	(2.24)	(2.01)			
$\Delta_M \ln K^{IT}_{t-4}$				0.010	0.0091			0.017***	0.024***	
				(1.44)	(1.13)			(3.13)	(3.93)	
$\Delta \ln K^{R\&D}{}_{t}$										0.007
										(0.24)
$\Delta_M \ln K^{R\&D}_{t}$	0.045***	0.047***	0.061*	0.045**	0.048*	0.038**	0.041	0.047***	0.053*	
	(2.79)	(2.74)	(1.93)	(2.55)	(1.69)	(2.22)	(1.54)	(2.62)	(1.77)	
$(P_N N^{PUB}/P_Q Q)_t$										1.59***
										(3.20)
$(P_N N^{PUB}/P_Q Q)_{t\text{-}1,\ M\text{-yr avg}}$	2.14***	2.44***	1.87**	2.44***	1.82**	2.36***	1.77**	2.55***	1.89**	
	(3.19)	(3.40)	(2.44)	(3.39)	(2.25)	(3.47)	(2.24)	(3.47)	(2.45)	
Year Dummies (Y / N)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Random / Fixed Effects / IV	RE	RE	RE	RE	RE	RE	RE	RE	RE	IV
Robust standard errors (Y / N)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	240	244	244	244	244	244	244	244	244	231
Number of countries	14	14	14	14	14	14	14	14	14	11

Notes to table: All regressions estimated using random effects with robust standard errors and include year dummies and a constant (not reported). t-statistics in parentheses. In all specifications the dependent variable is growth in TFP. Independent variables are: growth in capital services from total ICT equipment, telecommunications equipment (CT), IT hardware (IT) and private R&D; and the flow of public R&D in GDP. Column 1 includes total ICT equipment (IT & CT) as an explanatory variable, with ICT capital services and changes in TFP estimated using national accounts deflators. Column 2 is as column 1 but with ICT equipment capital services and TFP estimated using OECD harmonised deflators. All columns from 2 onwards experiment with short (1 year) and long (4 year) differences, but all estimated using the same sample. Columns 2 and 3 include ICT, private R&D and public R&D as explanatory variables, using one-year and four-year differences respectively. Columns 4 and 5 break ICT equipment out into capital services from CT and IT equipment. Columns 6 and 7 drop IT hardware. Columns 8 and 9 reinstate IT hardware and drop CT equipment. Finally, column 10 presents the second stage of an IV regression, where CT capital services growth is instrumented for in the first stage using instruments for the cost of capital, mobile termination charges and regulatory indicators for the telecommunications sector. Results for the first stage are presented in Appendix C.

more precise when lagging CT capital services by two periods and IT hardware by four periods.

Results in column 4, based on first differences and including CT and IT separately, suggest that the ICT result may be driven by CT, which is weakly significant at the 10% level. IT capital services are estimated as statitically insignificant. In column 5, we again increase the length of differences to four years. We find that neither CT or IT capital services are statistically significant, but we note that the coefficient on CT capital services is increased, whilst that on IT capital services is reduced.

In columns 6 and 7 we include CT and exclude IT, and again estimate using one-year and four-year differences. We find that CT capital services are significant at the 5% level, and moving from column 6 to 7, the esimated elasticity increases from 4% to 6%. The coefficient on private R&D is raised slightly, from 3.8% to 4.1%, but is no longer statistically significant. The coefficient on public R&D is reduced, as is its t-statistic, but remains very large.

In columns 8 and 9, we exclude CT capital services and replace it with IT capital services. Now we find that IT capital services are strongly significant at the 1% level, and increasing the length of the difference to 4 years raises the estimated elasticity from 1.7% to 2.4%. The pattern for private and public R&D is as in previous columns.

Thus, we present evidence of a correlation between TFP growth and capital services from ICT equipment, which is consistent with the presence of network effects or spillovers. We note the potential for measurment error in the disaggregation of ICT equipment and we find that disaggregation does indeed create two collinear variables. Thus we are unable to conclusively determine whether our result for ICT equipment is driven by CT equipment, IT hardware, or indeed both. Our results are however consistent with CT spillovers that can also be observed with (increased) error, from data for IT hardware or aggregate ICT equipment capital services.

These results were based on OLS regressions using lagged independent variables for reasons described above. However, for those readers who feel lagging those variables does not remove the issue of endogeneity, in the final column we take a different approach. We present the second stage of an IV regression, using contemporaneous terms.[29] Instrumenting for CT equipment, we estimate a positive correlation for CT capital services that implies a large excess elasticity of over 7%.

4.3 Robustness checks

In Table 2 we present a series of robustness checks. Our preferred specification, used in all columns, is that based on four-year differences. All regressions are estimated with robust standard errors and include year dummies.

[29] In the first stage we instrument for growth in CT capital services using data on the cost of capital, regulatory indicators for the telecommunications sector and mobile termination charges. See Appendix C.

In column 1 we present results that include country fixed effects. Running a Hausman test confirms that we ought to estimate with fixed effects, but we conduct most estimation using random effects due to the lack of within time-series variation in the flow of public R&D. Including country fixed effects raises our estimated elasticity for CT capital services to 7.3%, but it is less precisely estimated and only statistically significant at the 10% level. The estimated elasticity for private R&D is also raised to 10%. When country fixed effects are included we find that flow of public R&D is no longer statistically significant.

Scatter charts above show that the ICT correlations we are estimating seem to be at least party driven by observations for Finland and Sweden. In column 2 we revert to estimating with random effects but excluding observations for Finland and Sweden. We find that capital services from CT and private R&D are now both positive but statistically insignificant. Public R&D remains significant but continues to imply an enormous rate of return.

Years during and since the Great Recession have been characterised by low productivity growth in most advanced economies. TFP growth is also strongly influenced by cyclicality and unmeasured factor utilisation. The years for which the impact of such effects are likely greatest in the data are the years of the recession. Therefore, in column 3, we run the regression over the period 1990 to 2007, thus excluding the crisis and the post-recession period. As in column 2, we find that this reduces the magnitude of our coefficients on CT and private R&D capital services and renders them statistically insignificant. As shown in Figure 1, excluding the recession years actually excludes a decline in TFP growth which came shortly after a decline in growth of telecoms capital services. Excluding the post-recession period also excludes a small recovery in TFP which follows an increase in telecoms capital services.

Results in Basu et al. (2003) and various papers from Brynjolfsson (e.g. Brynjolfsson and Hitt (2003)) suggest that what appear to be supernormal returns to ICT equipment are actually returns to complementary intangible capital invested in after the initial ICT investment. With the exceptions of: software; R&D; mineral exploration and artistic originals; the growth decomposition from which our data derive did *not* include intangible capital as a factor of production. Therefore, in this data, the contribution of these other forms of intangible capital is an implicit component of TFP. In column 4 we include contemporaneous terms for growth in the three forms of intangible capital categorised in Corrado et al. (2005). Those terms are: a) software (and databases); b) innovative property (excluding R&D, thus including design and product innovation); and c) economic competencies (including workforce training as well as reputational and organisational capital). We find that this has little impact on our estimated coefficient for CT capital services, although it is less precisely estimated and is only significant at the 10% level. Interestingly, the inclusion of other forms of intangible capital not already capitalised in the national accounts renders our private R&D variable statistically insignificant, possibly suggesting complementarities between R&D and other forms of intangible capital. The weaker result for private R&D is also partly due to the exclusion of data for Ireland and Portugal, for whom we do not have data for our newly included intangible variables.[30] As shown in the scatter charts presented above, these are two countries where above time/country average growth in R&D capital services is associated with above time/country average growth in TFP. The estimated coefficients on those other intangible variables however do not show a statistically significant correlation between growth in TFP and intangible capital services, except in the case of innovative property (excluding R&D) where the correlation is actually negative. The result for software therefore does not provide any evidence consistent with network effects from that particular ICT asset. Similarly, Edquist and Henrekson (2016) also fail to find any statistically significant effects from software capital services on TFP.

[30] We also do not have intangible investment data for Belgium, hence the 11 countries included in the regression.

Table 2: Robustness checks

	(1)	(2)	(3)	(4)	(5)
	FE	Excl. FIN & SWE	Endpoint: 2007	Incl. intang	Non-overlapping
VARIABLES	$\Delta_4$lnTFP	$\Delta_4$lnTFP	$\Delta_4$lnTFP	$\Delta_4$lnTFP	$\Delta_4$lnTFP
$\Delta_4 \ln K^{CT}{}_{t-2}$	0.073*	0.022	0.040	0.044*	0.052**
	(2.00)	(0.77)	(1.41)	(1.72)	(2.51)
$\Delta_4 \ln K^{R\&D}{}_{t-5}$	0.10**	0.048	0.020	0.015	0.0033
	(2.52)	(1.48)	(0.48)	(0.39)	(0.12)
$(P_N N^{PUB}/P_Q Q)_{t-1,\ 4\text{-yr}}$	0.76	2.23**	1.50**	2.08**	1.72***
	(0.42)	(2.38)	(2.23)	(2.14)	(3.78)
$\Delta_4 \ln K^{SOFT}{}_t$				0.00034	
				(0.011)	
$\Delta_4 \ln K^{IP\ excl.\ R\&D}{}_t$				-0.088**	
				(-2.03)	
$\Delta_4 \ln K^{EC\ COMP}{}_t$				0.081	
				(1.44)	
Year Dummies (Y / N)	Y	Y	Y	Y	Y
Random / Fixed Effects	FE	RE	RE	RE	RE
Robust standard errors (Y / N)	Y	Y	Y	Y	Y
Observations	244	210	160	163	58
R-squared	0.478				
Number of ctrycode	14	12	14	11	14

Notes to table: All regressions using long (four-year) differences, estimated with robust standard errors and include year dummies and a constant (not reported). t-statistics in parentheses. In all specifications the dependent variable is growth in TFP. Independent variables are: growth in capital services from telecommunications equipment (CT), IT hardware (IT) and private R&D; and the flow of public R&D in GDP. Column 1 includes country fixed effects. Columns 2 excludes observations for Finland and Sweden. Column 3 is estimated using an endpoint prior to the crisis (2007). Column 4 includes measures of other intangible capital services as controls, including software, innovative property excluding R&D and economic competencies, based on the Corrado, Hulten and Sichel (CHS) (2005) framework. Columns 5 uses non-overlapping four-year differences.

All results presented so far based on long differences include overlapping observations. Therefore in column 5 we present results of estimation when we only include non-overlapping observations. We find that our CT result is robust to this change, with an estimated elasticity of 5.2%, but that private R&D is no longer statistically significant and enters with a much reduced coefficient. Public R&D remains strongly significant. The result in column 5 is a strong one as, we note, it is only based on 58 observations.

4.4 Using longer differences to adjust for measurement error in explanatory variables

In Table 1 we estimate correlations between growth in TFP and a set of explanatory variables based on first differences and also longer differences. We find that increasing the length of the difference raises the coefficients on (certain) explanatory variables. Our estimated CT-output elasticity is raised from 4% using first differences (column 7, Table 1), to 6% (column 8), whilst that on IT is raised from 1.7% (column 9) to 2.4% (column 10). For private R&D, our estimated elasticity is raised but less substantially, whilst the estimated rate of return to public R&D is reduced.

Thus our results, particularly in the case of CT and IT equipment, are consistent with the classical measurement error scenario, where measurement error introduces noise to the explanatory variable and results in a downward bias to the estimated coefficient.

In Table 3 we present estimates for the terms discussed in section 3.3. Column 1 is the explanatory variable,[31] column 2 is the number of differences taken in the estimation (i.e 1 is first differences, 2 refers to two-year differences etc.), column 3 is the estimated coefficient,[32] column 4 is the share of variance in the variable accounted for by measurement error, and column 5 is the factor described in section 3.3, which is used to adjust the coefficient. Finally, in column 6 we adjust each coefficient. In the final row we take an average of these adjusted values to form our final preferred estimate of the CT elasticity, which is 8.6%, more than double the reported coefficient based on first differences.

4.5 Summary of results

In summary, we generate statistically significant correlations between TFP and ICT equipment, CT equipment, IT equipment, private R&D and public R&D. The pattern of results is supportive of the hypothesis that, in the case if ICT equipment, the result is driven by CT capital, but that measurement error means the result can also be observed using data for ICT equipment or even IT hardware equipment. But, strictly speaking, our variables for CT and IT equipment are collinear and we are unable to determine which is driving the result. Our CT result is suggestive of an excess elasticity in the range of 3% to 9% and is robust to certain changes in specification, including the use of fixed/random effects and the use of longer differences. It is not however robust to excluding data for the 1990's or the late 2000's, or to the exclusion of data for Finland and Sweden.

Similarly we generate a statistically significant effect for IT hardware, which is somewhat dependent on using a longer lag structure (three or four lags). The coefficient is also much smaller in magnitude than

[31] In this table we only present results for CT capital services. We did conduct the same exercise for IT hardware, private and public R&D but those estimates are not reported here. In the case of public R&D we estimated that the share of variance in public R&D accounted for by measurement error (i.e. column 4) is greater than 0.5. As a result, the term in column 5, which we use to adjust the coefficient, is negative. For private R&D, we are able to perform the calculation but the adjustment is very small, because only a very small fraction of the variance in R&D capital services is accounted for by measurment error.

[32] Estimated using the number of differences reported in column 2, including year dummies and using random effects.

Table 3: Long differences: adjustment for measurement error in explanatory variables

(1)	(2)	(3)	(4)	(5)	(6)
variable (X)	M (no. of diffs)	$\hat{\beta_M}$	$\frac{\sigma_m^2}{Var(\Delta_M ln\tilde{X})}$	$1-\frac{2\sigma_m^2}{Var(\Delta_M ln\tilde{X})}$	$\hat{\beta_M}$(Adj)
$\Delta \ln K^{CT}{}_{t-2}$	1	4.0%			
$\Delta \ln K^{CT}{}_{t-2}$	2	5.2%	0.15	0.70	7.4%
$\Delta \ln K^{CT}{}_{t-2}$	3	5.6%	0.16	0.68	8.3%
$\Delta \ln K^{CT}{}_{t-2}$	4	6.0%	0.18	0.65	9.2%
$\Delta \ln K^{CT}{}_{t-2}$	5	6.1%	0.18	0.64	9.6%
Final estimate (average β)		5.4%			***8.6%***

Notes to table: All regressions include period dummies and a constant, and are estimated using random effects with robust standard errors. Column 1 is our explanatory variable of interest. Column 2 is the number of differences (of dependent and explanatory variables) taken in the estimation. Column 3 is the estimated coefficient. Column 4 is the share of the variance in X accounted for by measurment error. Column 5 is the adjustment factor. Column 6 is the adjusted coefficient, estimated as (3)/(5). The final row is an average of the coefficients reported in columns 3 and 6.

those for CT or R&D, and suggests an elasticity in the range of 1% to 3%. For private R&D we estimate an elasticity of approximately 4% to 10%. For public R&D we estimate a rate of return of well over 100% in all specifications which seems to be an overestimate.

Thus our result on IT is somewhat supportive of the conclusions presented in Brynjolfsson et al. (2002) and Basu et al. (2003) who find larger returns to the accumulation of IT capital with longer lags, which may be because spillovers take time, or may be because full appropriation of the returns to IT requires the accumulation of complementary intangible capital, which also takes some time. Note that Brynjolfsson et al. (2002) suggests lags of five to seven years, and Basu et al. (2003) suggest five to fifteen years. The lag used here lies at the lower end of this range.

Thus we conclude that inclusion of data for the early 1990s (network build-out) and the late 2000s is essential in seeking any correlation between growth in TFP and growth in telecoms capital services. When we experiment with longer differences, we find that the coefficients on CT or IT capital services and public R&D are raised, whilst that on private R&D is also raised but less substantially. The implications of our results using longer differences are therefore consistent with those reported in Goolsbee (2000), that is, if there is measurement error in the explanatory variables, coefficients based on first differences are biased downward.

As we have already noted, in the case of estimating telecoms capital services, there is uncertainty around the level of actual CT investment, the level of the stock and the price of investment. There is also of course error in the measurement of knowledge flows due to investment in public scientific research. An interesting and possibly surprising finding is that these results suggest that there is considerably less measurment error in capital services from IT and (private R&D).

In what follows we base our analysis using the mean adjusted coefficient reported in the final row of Table 3.

5 Economic Significance

Above we have reported a statistically significant correlation between growth in TFP and growth in CT capital servicesn. We also carry out an adjustment to our coefficient (elasticity) to correct for measurement error in CT capital services. But what is the economic significance of our results?

Table 4: Economic significance: contribution of CT capital services, 1990-2007

(1)	(2)	(3)	(4)	(5)
Country / Group	**ΔlnTFP**	**ΔlnK^{CT}**	**Spillover**	**% of TFP explained**
AUT	1.18%	6.32%	0.54%	46.2%
BEL	0.11%	7.49%	0.64%	591.7%
DNK	0.29%	5.67%	0.49%	168.6%
ESP	-0.69%	4.33%	0.37%	
FIN	2.08%	17.70%	1.52%	73.1%
FRA	0.58%	8.97%	0.77%	132.0%
GER	0.89%	3.22%	0.28%	31.2%
IRL	0.80%	9.34%	0.80%	100.1%
ITA	0.24%	4.06%	0.35%	146.8%
NLD	0.65%	-0.01%	-0.00%	
PRT	0.49%	10.63%	0.91%	186.8%
SWE	1.06%	14.74%	1.27%	119.9%
UK	0.72%	6.88%	0.59%	82.1%
N. Europe (large)	0.72%	4.99%	0.43%	59.9%
N. Europe (small)	0.73%	4.06%	0.35%	47.6%
Scand	1.51%	9.30%	0.80%	52.9%
S. Europe	-0.08%	4.23%	0.36%	
US	0.49%	7.23%	0.62%	128.2%
EU-13	0.51%	5.61%	0.48%	94.4%
All countries	0.49%	6.47%	0.56%	112.6%
EU-10 (excl. ESP, ITA, PRT)	0.74%	6.13%	0.53%	71.7%

Notes to table: Data are estimates for the years 1990-2007. Econometric parameters estimated over 1990-2013. Column 1 presents the countries in our dataset. Column 2 presents mean TFP growth (estimated as the change in the natural log) over the years 1990 to 2007 for which data are available (for some countries our TFP data begin later than 1990). Column 3 presents estimates of growth in CT capital services over the same years for which data are available. Column 4 presents our estimate for the contribution of CT spillovers, estimated as the elasticity (7.1%) multiplied by growth in capital services. Column 5 presents the percentage of TFP explained by the CT spillover estimate, estimated as the latter divided by the former. We are unable to estimate for countries for which mean TFP growth is negative. In the final rows we present weighted estimates for country groups, the EU-13 and All (14) countries in our dataset, with US data presented as a benchmark. Country groups constructed as: 1) North Europe (large), consisting of FRA, GER, UK; 2) North Europe (small), AUT, BEL, IRL, NLD; 3) Scandinavia, DNK, FIN, SWE; 4) Southern Europe, ESP, ITA, PRT.

We answer that in Table 4, which is set out as follows. Column 1 presents the fourteen countries in our dataset, as well as some country-group aggregates constructed to aid comparison. Column 2 is mean TFP growth calculated over the period 1990 to 2007.[33] We choose to perform this calculation over the 1990-2007 period as TFP is strongly negative during the recession. This pulls down average TFP growth quite substantially and means that if we were to use 1990-2013 data, a much larger proportion of TFP would be potentially explained by CT spillovers. As explained above, we are seeking to uncover the permanent relationships between TFP growth and our explanatory variables. Therefore we remove the period for which our dependent variable is predominantly influenced by cyclicality. Column 3 is mean growth in CT capital services, calculated over the same period.[34] In column 4 we present an estimate of the mean contribution of CT spillovers in that country, estimated as the CT output elasticity (8.6%, Table 4) times (mean) growth in CT capital services (column 3). In column 5 we present the percentage of TFP growth explained by the CT spillover contribution, estimated as the spillover contribution (column 4) over TFP growth (column 2). We note that for some countries, such as Spain, TFP growth is negative so we are unable to carry out this calculation. Finally, in column 6 we present estimates of the total social rate of return to investment in CT equipment using the (average) elasticity estimated econometrically and estimates of the real capital stock and real value-added in each country in 2013.

To summarise Table 4, column 2 presents mean TFP growth for each country (or country group) over the

[33] For some countries, our data on growth in TFP begin in 1990 and for others they begin later (BEL (1999), DNK (1996), GER (1995), IRL (1999), PRT (1999), SWE (1997)). Mean TFP is therefore estimated over the years 1990 to 2007 for which data are available.

[34] For growth in CT capital services, we have data from 1990 for all countries, with the exception of: BEL (1996); GER (1992); IRL (1996); PRT (1996); SWE (1994). Again, we estimate over the years 1990 to 2007 for which data are available.

period 1990 to 2007, ranging from -0.69% pa in Spain to 2.08% pa in Finland. On average, weighted TFP growth in the EU-13 was 0.51% pa, compared to 0.49% pa for the US. However, as shown, the EU-13 figure is pulled down by data for Southern Europe. Looking at European country groups, TFP growth ranged from -0.08% pa in the South (ESP, ITA, PRT), to 0.72% pa in large North European economies (FRA, GER, UK), 0.73% pa in small North European economies (AUT, BEL, IRL, NLD), and 1.51% in Scandinavia (DNK, FIN, SWE).

Column 3 presents mean growth in CT capital services over the same period, which range from approximately zero in the Netherlands to 17.7% pa in Finland and 14.8% in Sweden. Mean (share-weighted aggregate) growth in capital services in the EU-13 was 5.6% pa over the period, compared to 7.2% pa in the US. Using our estimated CT-output elasticity of 8.6%, we estimate a contribution to growth of CT spillovers of between 0% pa in the Netherlands and 1.52% pa in Finland (column 4). The spillover contribution in the EU-13 is estimated at 0.48% pa, compared to 0.62% pa in the US.

Our estimates suggest that CT spillovers could explain approximately 94% of TFP growth in the EU-13. Our estimates overexplain TFP growth in the fourteen country aggregate (113%) and the US (128%), although we note that other factors or determinants may be negatively associated with TFP growth. In addition, as already noted, the EU-13 figure is distorted by data for Southern Europe. Using data for country groups, in small North European economies we estimate that telecoms spillovers explain 48% of TFP growth, compared to 53% in Scandinavia and 62% in the larger North European economies. In absolute terms, telecoms spillovers are estimated as largest in the Scandinavian countries, at 0.8% pa.

Since our estimates are somewhat distorted by very low TFP growth in the South European countries, in the final row we present estimates for the EU-10, that exclude data for Spain, Italy and Portugal. For this group we estimate mean TFP growth of 0.74% pa, of which 0.53% pa (72%) can be explained by estimated CT spillovers or network effects.

Thus our estimates explain the majority of, and in some cases overexplain, TFP growth. This is a reflection of the high estimated CT-output elasticity of 8.6%.[35] We note that excluding the earlier years of the sample considerably reduces the estimated elasticity.[36] Thus these high estimates appear to only be associated with the earlier years of data, which are the years of network build-out and fast adoption among users.[37]

[35] So far we have discussed our results in terms of the elasticity but we have not said anything about the rate of return. The elasticity and estimate of the (CT) capital-output ratio can be used to generate a rate of return but it will be incorrect, due to the error in measuring CT capital. First, network investment builds on infrastructure created over a century ago, which our capital data may not fully (accurately) reflect. Second, as noted in our model, the network includes firms but also consumers. Thus our measure of (access) capital is mismeasured and underestimated to a large degree. To highlight this, using our estimate of the (average) elasticity of 8.6%, and the average CT capital-output ratio (of 0.0385), we estimate a social rate of return of 223%. If however K^{CT} were 3 times larger (due to underestimation of network and access capital), the implied social rate of return would be in the region of 75%. As set out in the model, rather than estimate with capital services we ought to estimate with share-weighted capital services (i.e. the contribution). However, when we did this we found it to be statistically insignificant and we know the share to be mismeasured. The coefficient (of $(1/1\text{-}\gamma)$) was 1.4, implying a social rate of return to CT capital that is 5 times the private rate of return.

[36] Running our baseline specification (two-year lag, RE, long (4-year) differences) over the full period gives an estimated elasticity of 6%. Interpreting the rate of capital services growth in Figure 1, it seems that most of the growth in CT capital occurred before 2001, with a second run of growth that ended in 2007. Running the same regression for years before and after 2007 gives an estimated elasticity of 4% before 2007 with a t-stat of (1.41), compared to -0.008% (-0.23) post-2007. Using 2001 as the cut-off point, we estimate a coefficient of 4.2% (1.93) prior to 2001, and 3.1% (0.91) post-2001.

[37] Interestingly, we note that in a study on the returns to public infrastructure (roads), Fernald (1999) estimates a similarly very high elasticity and rate of return. He notes that these effects apply to the early years after the completion of the interstate highway system and that marginal effects declined thereafter. Analagously, we suggest that the returns to build-out and adoption of internet and mobile connectivity in the 1990s and early 2000s were likely larger than the returns to further investments later in the period.

6 Conclusions

In previous work (Goodridge et al., 2016a) we have documented the contribution to growth of ICT capital, and in particular communications (CT) equipment, in both the US and Europe over the period 1995 to 2013. In this paper we seek to estimate whether there is also an indirect effect from growth in CT capital input on total factor productivity via network effects, or spillovers, over a similar time period.

Using an international growth-accounting dataset composed of the US and thirteen European countries, we look for evidence consistent with spillovers derived from the accumulation and deployment of CT equipment. Within that, our model also incorporates potential spillovers from IT hardware (as either distinct or as a result of mismeasurement) and activity in R&D, both private R&D conducted by firms and also public R&D. Our findings are as follows.

First, we find evidence of a statistically significant correlation between lagged growth in CT capital services and TFP, which is consistent with the presence of network effects or spillovers. Using longer differences we also show how error in the measurement of CT captal services can introduce a downward bias to estimated coefficients. Adjusting for that error we estimate an output elasticity of 8.6%, over and above the share of CT costs in production. We note however that our results are not robust to: a) exclusion of data for the 1990's or late 2000's; b) exclusion of data for Finland and Sweden. Our results are also economically significant. Using our estimated output elasticity for CT, we estimate that CT spillovers potentially explain: 39% of TFP growth in small North European economies; 44% in Scandinavian economies; and 50% in larger North European economies. Our comparable estimate for the US is 106% of TFP growth.

Second, we find some evidence consistent with spillovers from IT hardware, although typically with a smaller elasticity than estimated for CT capital input, which is consistent with measurment error in the explanatory variable. We estimate an IT excess elasticity in the order 1% when we apply a lag of three to four years. Thus, our results suggest, first, that such effects may reflect mismeasurement in the disaggregation of investment in ICT equipment. Second, if the IT effect is distinct, our evidence suggests that it operates with longer lags, which is consistent with other findings in the literature including for instance, Basu et al. (2003) and Brynjolfsson and Hitt (2003).

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A Appendix

As noted in the main text, we estimate using random effects. This is for two principal reasons: first, random effects are more appropriate in the context of public R&D, since the majority of variation is between, rather than within, countries; and second, since we are using differences, it is often argued that it is no longer necessary to include fixed effects.

However, even in a model based on growth, it seems reasonable to argue that there are still country-specific fixed effects in differenced data. Running a Hausman test on our preferred specification also confirms that we ought to estimate with fixed effects. In the table beow, we repeat our main results, but this time all estimated using country fixed effects.

Table 5: Regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ICT: NA Defs	ICT: OECD HDs	ICT	IT & CT	IT & CT	CT	CT	IT	IT
	Short (M=1)	Short (M=1)	Long (M=4)	Short (M=1)	Long (M=4)	Short (M=1)	Long (M=4)	Short (M=1)	Long (M=4)
VARIABLES	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP	$\Delta_M$lnTFP
$\Delta_M \ln K^{ICT}{}_{t\text{-}3}$	0.042**	0.040***	0.049***						
	(3.04)	(3.28)	(3.66)						
$\Delta_M \ln K^{CT}{}_{t\text{-}2}$				0.044	0.057	0.054*	0.073*		
				(1.66)	(1.42)	(2.08)	(2.00)		
$\Delta_M \ln K^{IT}{}_{t\text{-}4}$				0.014*	0.015			0.022***	0.030***
				(2.15)	(1.68)			(4.00)	(6.27)
$\Delta \ln K^{R\&D}{}_{t\text{-}5}$	0.10***	0.12***							
	(3.41)	(3.30)							
$\Delta_M \ln K^{R\&D}{}_{t\text{-}5}$			0.12**	0.12***	0.12**	0.11***	0.10**	0.11***	0.11**
			(2.57)	(4.30)	(2.90)	(3.97)	(2.52)	(3.77)	(2.76)
$(P_N N^{PUB}/P_Q Q)_{t\text{-}1}$	2.42	2.50							
	(1.42)	(1.39)							
$(P_N N^{PUB}/P_Q Q)_{t\text{-}1,\ M\text{-}yr\ avg}$			0.83	2.27	0.56	2.07	0.76	2.03	-0.020
			(0.52)	(1.27)	(0.32)	(1.15)	(0.42)	(1.14)	(-0.010)
Year Dummies (Y / N)	Y	Y	Y	Y	Y	Y	Y	Y	Y
Random / Fixed Effects	FE	FE	FE	FE	FE	FE	FE	FE	FE
Robust standard errors (Y / N)	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	240	244	244	244	244	244	244	244	244
R-squared	0.529	0.511	0.481	0.562	0.489	0.557	0.478	0.550	0.449
Number of ctrycode	14	14	14	14	14	14	14	14	14

Notes to table: All regressions estimated using fixed effects with robust standard errors and include year dummies and a constant (not reported). t-statistics in parentheses. In all specifications the dependent variable is growth in TFP. Independent variables are: growth in capital services from total ICT equipment, telecommunications equipment (CT), IT hardware (IT) and private R&D; and the flow of public R&D in GDP. Column 1 includes total ICT equipment (IT & CT) as an explanatory variable, with ICT capital services and changes in TFP estimated using national accounts deflators. Column 2 is as column 1 but with ICT capital services and TFP estimated using OECD harmonised deflators. All columns from 2 on experiment with short (1 year) and long (4 year) differences, but all estimated using the same sample. Columns 2 and 3 include ICT, private R&D and public R&D as explanatory variables, using one-year and four-year differences respectively. Columns 4 and 5 break ICT equipment out into capital services from CT and IT equipment. Columns 6 and 7 drop IT hardware. Finally, columns 8 and 9 reinstate IT hardware and drop CT capital services.

B Appendix

Briefly, missing data on GFCF in intellectual property products (IPPs, i.e. software, R&D, artistic originals and mineral exploration) were filled in making use of the IPP total and calculating GFCF in other assets as a residual, including if necessary, using the share of GFCF in a particular asset in previous years and the IPP total to impute estimates for missing years. Where data for mineral exploration and artistic originals remained missing, these were replaced using values for the same series from either Intan-Invest (Corrado et al., 2012) or EUKLEMS (O'Mahony and Timmer, 2009). Note, data from Intan-Invest are for the market sector, so we necessarily assume that the market sector makes all investments in these two assets, as opposed to any government investment.

In the OECD.Stat data, ICT equipment is defined as the aggregate of IT hardware and CT equipment and so does not include software. Where data on GFCF in IT or CT were missing, data were either estimated as a residual using total GFCF in ICT equipment, or imputed using the estimate of total GFCF in ICT equipment and a moving average of the component share for either IT or CT. Where ICT (or IT/CT) equipment remained missing, we used the ratio implied in the EUKLEMS data to extrapolate and/or impute. In the case of Germany, a split into IT and CT equipment is unavailable in the official data. Therefore, for this country, pre-2007 GFCF in IT and CT equipment is taken from EUKLEMS. Post-2007 data were imputed using ICT GFCF as a share of GDP in 2013, taken from the OECD Science, Technology and Industry Scoreboard 2015 (OECD, 2015), changes in gross value-added, and the share of CT GFCF in ICT equipment. Similarly for other assets/countries, for years where GFCF data were missing, data were imputed using the profile of the same respective series in EUKLEMS. Where data on GFCF in R&D were missing, data were extrapolated or imputed using cross-country data on Gross Expenditure on R&D (GERD), downloaded from the OECD. Imputed data make use of the ratio between R&D GFCF and GERD in countries where both series' are available. We exclude GFCF in dwellings which are not capital in the context of productivity analysis.[38]

UK data on nominal GFCF in CT equipment were taken from OECD.Stat, in turn from the UK national accounts. We note that the estimate for investment in CT equipment in the UK is, by some distance, the smallest of all large, advanced European economies, and is considerably lower than in a number of much smaller economies. Official estimates for the UK are also in stark contrast to estimates from our previous work (Goodridge et al., 2013) (hereafter, GHW) and those in EUKLEMS (both estimated using previous vintages of the Input-Output Supply and Use tables (SUTs)). A comparison of official UK estimates with those in GHW and EUKLEMS is presented in Goodridge et al. (2016a). They show that the latest revised UK data do not incorporate the dramatic run-up of investment in the late 1990s as observed in GHW, interpreted there as the creation of network infrastructure, and also EUKLEMS. In comparison the official series is flat, with a clear level difference of at least £2bn for most of the period reported. In 2001, the peak of UK telecoms investment, the difference between GHW and the latest official estimates is as much as £5.6bn. The difference between EUKLEMS and official estimates is even greater. We therefore use estimates from GHW as an alternative series for UK investment in CT equipment, with estimates extrapolated forward (from 2009) using growth rates taken from the official series.

The GFCF price index for each asset, and the value-added price index, were derived implicitly using

[38] Strictly, for consistency, we should therefore also exclude the output of the real estate sector from GVA, since this is largely made up of the actual and imputed rents (for owner-occupiers) of dwellings. However data on the output of the real estate sector were not available for all countries. We therefore use total economy GVA including actual and imputed rents for each country, but note this issue in our data and estimation.

constant and current price data, and the price index re-referenced to 2005=1. Nominal GFCF and the corresponding price index were then extrapolated using data from EUKLEMS where available, and the constant price series' re-estimated using the re-referenced price index. Where national price indices for either software, or mineral exploration and copyrights, were missing or unavailable, we either applied the aggregate price index for IPPs, or extended the asset price index using the aggregate price index for IPPs for that country. To deflate GFCF in R&D, we used each country's gross value-added price index. Where data for the US were missing, GFCF price indices were downloaded directly from the BEA. For Sweden, GFCF price indices were extended using data downloaded from Statistics Sweden.

For capital stock initial values, where we had estimates from EUKLEMS, the initial value (re-based to 2005 prices) from EUKLEMS was used. Where we had no information from EUKLEMS (e.g. as for R&D), the initial value was estimated using the standard steady-state formula, $K_t = I_t/(g + \delta)$, where g is mean growth in real investment and δ is the asset-specific depreciation rate. Growth in capital services by country is thus estimated as share-weighted growth in capital services from different assets, as in equation (**??**), where the shares are asset user costs as a share of total economy gross operating surplus as in equation (**??**), and ρ is estimated ex-post such that user costs exhaust total gross operating surplus.

Regarding labour, the share of labour payments in GVA is taken directly from the Total Economy Database (TED) produced by The Conference Board, the reason being that OECD (NSI) data on Compensation of Employees do not include any element of the mixed income earned by the self-employed. The TED data on labour shares do however include an estimate of the labour renumeration (from within mixed income) earned by the self-employed, as does EUKLEMS, which we use to backcast the TED labour share. For consistency, and to incorporate data on growth in labour services and therefore labour composition, all labour input data are taken from TED, with growth in annual person-hours worked benchmarked in levels to OECD (NSI) data in 2013. If labour types are paid (in proportion to) their marginal products then the index of labour services (times the labour share) captures entirely the per hour contribution of skill changes and hence does not affect TFP (since TFP is calculated by subtracting off this from output growth). The capital per hour terms are analogous: growth in different capital types per hour, weighted by their rental shares, giving composition-adjusted growth in total capital services per hour. Finally, Data on GVA are nominal and real at basic prices, backcast using EUKLEMS where available. When we switch between alternative deflators for ICT assets, we make a corresponding adjustment to the value-added price index, so that real gross value-added incorporates the change to real GFCF.

C Appendix

Below we present results from two IV regressions. The first two columns present the first and second stage of the regression presented in Table 1, where we instrument for CT capital services. A description of instruments is provided in the table notes. The final three columns present the first and second stages of a second regression where we instrument for capital services from both CT and IT equipment. As shown in the final row, instrumenting for both variables results in weaker identification in the first stage.

Table 6: Instrumental Variables, 1990-2013

	IV 1, Stage 1	IV 1, Stage 2	IV 2, Stage 1	IV 2, Stage 1	IV 2, Stage 2
	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\Delta\ln K^{CT}$	$\Delta\ln TFP$	$\Delta\ln K^{CT}$	$\Delta\ln K^{IT}$	$\Delta\ln TFP$
TAF^{M}	-0.151		-0.151	-0.237	
	(0.170)		(0.170)	(0.233)	
ΔTAF^{M}	0.231		0.231	0.647	
	(0.203)		(0.203)	(0.464)	
r	-0.00459**		-0.00459**	-0.00930***	
	(0.00185)		(0.00185)	(0.00300)	
Δr	0.00359*		0.00359*	0.00357	
	(0.00202)		(0.00202)	(0.00332)	
Termination charge	0.0715		0.0715	0.00520	
	(0.142)		(0.142)	(0.253)	
ΔTermination charge	-0.156*		-0.156*	-0.0943	
	(0.0942)		(0.0942)	(0.159)	
Entry	-0.00493		-0.00493	-0.0234*	
	(0.00793)		(0.00793)	(0.0142)	
ΔEntry	0.00439		0.00439	0.00156	
	(0.00580)		(0.00580)	(0.00744)	
Market Structure	-0.0231**		-0.0231**	-0.000204	
	(0.00990)		(0.00990)	(0.00702)	
ΔMarket Structure	0.0155***		0.0155***	-0.0354*	
	(0.00410)		(0.00410)	(0.0192)	
$\Delta\ln K^{R\&D}$	0.634**	0.00702	0.634**	0.127	-0.00670
	(0.307)	(0.0289)	(0.307)	(0.106)	(0.0354)
$(P_N N^{PUB}/P_Q Q)_t$	2.973	1.588***	2.973	-1.994	1.482***
	(3.937)	(0.496)	(3.937)	(2.582)	(0.505)
$\Delta\ln K^{CT}$		0.0726***			0.0985**
		(0.0262)			(0.0414)
$\Delta\ln K^{IT}$					-0.0256
					(0.0209)
Observations	231	231	231	231	231
R-squared		0.131			0.075
F-test		50.96			10.10

Notes to table: All regressions estimated with robust standard errors (in parentheses) and include year dummies. Table presents the first and second stages of two IV regressions. Column 1 is the first stage of the regression presented in Column 10 of Table 1, where we instrument for CT capital services. Column 2 repeats the second stage of that regression. Columns 3 and 4 are the first stage of a second regression, where we instrument for capital services from both CT and IT equipment in the first stage. Column 5 is the second stage. Our exogenous instruments are the level of, and change (Δ) in: the tax adjustment for machinery and equipment (incl. ICT equipment) (TAF^{M}); the lending interest rate; mobile termination charges; and OECD regulatory indicators on ease/degree of entry and market structure/competitiveness. We also include, as controls, IT hardware and (private) R&D capital services and the public R&D to GDP ratio. The dependent variable in the second stage is growth in TFP.