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Do Capital Incentive Policies Distort the Adoption of Cloud Technologies and Big Data?

Timothy DeStefano, Nick Johnstone, Richard Kneller, and Jonathan Timmis

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DO CAPITAL INCENTIVE POLICIES DISTORT THE ADOPTION OF CLOUD TECHNOLOGIES AND BIG DATA?[1]

Timothy DeStefano

Harvard Business School

Nick Johnstone

IEA

Richard Kneller

University of Nottingham

Jonathan Timmis

IFC - World Bank Group and University of Nottingham

Abstract

Cloud computing presents a significant change in the way firms access digital infrastructure – as an online service. Yet, policies that encourage digital diffusion are still targeted towards investment in physical IT capital. This paper takes advantage of a UK tax incentive for capital investment to examine firm adoption of cloud computing and big data analytics. Using a quasi-natural experimental approach our empirical results show that the policy increased investment in IT capital and hardware as one would expect; but it reduced the adoption of cloud and big data. For small firms and for big data the effects are particularly pronounced.

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Contact: tdestefano@hbs.edu, richard.kneller@nottingham.ac.uk, nick.johnstone@iea.org, jtimmis@ifc.org jonathan.timmis@nottingham.ac.uk

I. INTRODUCTION

Traditionally, firms adopted digital technologies by making significant up-front investments in hardware and software, which were then maintained by teams of IT specialists. Recently, there has been a change in the nature of IT. Now, firms increasingly acquire their data storage, processing and software needs as a service from third party providers offering "on demand" or "pay as you go" subscriptions. The growth of this new way of accessing IT, labelled the cloud, has been rapid (Van Ark, 2016; OECD, 2015). Cloud services were first launched by Amazon Web Services in 2006 and since 2009 cloud expenditures have grown at a rate 4.5 times faster than that on traditional IT investment (Forbes, 2017). By 2016, it is calculated that 30% of firms used cloud across the OECD, with expenditure on cloud services representing 25% of firms' IT budgets (Eurostat, 2018; Deloitte, 2017).

Despite these developments, in many countries policies to encourage digital diffusion are still targeted towards investments in physical forms of IT capital. Every country within the OECD for example, has some form of capital incentive policy, including tax allowances, subsidies, grants relating to IT hardware and software or tangible capital investments more generally (Tax Foundation, 2018). Such tax schemes are designed to stimulate IT investment by decreasing the user cost of capital (Jorgenson, 1963; Hall and Jorgenson, 1967) and/or by relaxing financial constraints.[2] Several of these schemes explicitly target smaller firms, since they are likely to face more severe credit constraints than larger firms.

To the extent that cloud services and traditional IT capital are substitutes, capital investment policies have the potential to discourage the adoption of cloud technologies. While important in itself, this may potentially affect the growth of the online IT services industry and there are reasons to anticipate that their

[2] Such schemes are often applied during periods of an economic slowdown. They may of course, also have an effect on growth in the medium- to long-run. There is also considerable empirical evidence that such schemes are effective, see for example Cummins et al. (1994), House and Shapiro (2008), Zwick and Mahon (2017), Ohrn (2018) and Maffini et al. (2019).

effects are more far reaching, creating a distortion that impedes the growth of small or young firms and the adoption of complementary technologies.

A nascent academic literature has begun to show cloud technologies are distinct from past waves of information technology, disrupting business models and economic outcomes. Previous digital technologies typically incurred large sunk costs and therefore favoured large firms with large scale over which to spread these costs (Calvino, DeStefano and Timmis, 2017; Calvino, Criscuolo and Menon, 2016; Brynjolfsson et al., 2008).[3] In contrast, purchasing IT services through the cloud shifts IT expenditures from a fixed to a largely variable cost, favouring the growth of young, credit-constrained firms who can adjust their IT needs quickly in response to the demand shocks they face. Bloom and Pierri (2018) find for example, that the adoption of cloud is occurring at a faster rate amongst young and small business entities than previous IT technologies. Jin and McElheran (2017) find evidence that purchases of IT services are related to significantly higher survival and growth among young plants. In addition, DeStefano, Kneller and Timmis (2019) find evidence that cloud adoption leads to faster employment and sales growth for young firms and to the reorganisation of older firms.[4] Cloud technologies therefore provide growth opportunities for the same type of firms that are often the target of capital incentive policies.

An assessment of the effect of capital incentive policies based solely on the substitution of physical IT for cloud, ignores complementarities across related IT technologies (McKinsey, 2011, 2017). The label 'cloud computing' in fact includes online access to various forms of IT hardware and software – such as access to storage, databases, processing, software and email. Yet, how those broader IT adoption decisions respond to capital incentive programmes is unknown. Such policies might further affect newer data-dependent technologies that rely on cloud, including big-data analytics, data driven decision making or artificial intelligence, that are anticipated by many to be important for future growth (McKinsey, 2011; Brynjolfsson and McElheran, 2016; Brynjolfsson et

[3] For example, advances in Enterprise Resource Planning (ERP) systems enabled the headquarters of large multinational corporations to co-ordinate and profit from complex, globally-fragmented production networks (OECD and World Bank, 2015).
[4] This occurs through closing plants and moving employment further from the headquarters

al. 2018; Economist, 2018; Niebel, Rasel and Viete, 2019).[5] This shift towards data driven business models is expected to follow increases in the stock of globally stored data from 33 zettabytes in 2018 to 175 zettabytes by 2025, much of which is expected to be stored and analysed using the cloud (Patrizio, 2018).

In this paper, we use the lens of a capital incentive programme to provide the first quantitative assessment of their effect on the diffusion of various cloud technologies and big-data analytics amongst firms.[6] For this task we take advantage of a particular tax incentive for physical capital investment in the UK – the Annual Investment Allowance (AIA).[7] The AIA was introduced in the financial year 2008-2009 with the explicit aim of increasing capital investment, and modified several times thereafter (in 2011 and 2014). The AIA allowed firms to deduct the cost of investment in capital against profits up to a certain threshold. It is particularly salient for our question as it coincides with the arrival of cloud services in the UK.[8] We exploit this policy change along with detailed firm-level data on the adoption of cloud computing, big-data analytics as well as their investment in various types of IT and non-IT capital.

We leverage the introduction and subsequent changes to the AIA as a quasi-natural experiment, which impacted the marginal investment costs of firms differently above and below tax allowance thresholds, affecting the incentive to adopt cloud technologies by treated firms.[9] The variation in AIA over time allows us to examine within-firm changes in response to changes in the AIA threshold. However, as firms can adjust their investment in response to the AIA, this poses a potential selection problem. To mitigate this issue, we follow the empirical approach previously applied to examine the effects of employment

[5] Definitions of AI/big data are plentiful. McKinsey (2017) define 5 areas of AI (autonomous vehicles, computer vision, language, virtual agents, and machine learning), share the joint feature that they are based on algorithms that learn from data without relying on rules-based programming in order to draw conclusions or direct an action.

[6] This work complements recent research by Brynjolfsson and McElheran (2016) which document the diffusion and adoption activities of data-driven decision making in the US.

[7] The threshold was £50,000. Within our data this value of investment was close to the 19th percentile of the distribution of total investment for 2008.

[8] The cost to the public finances of this policy was also significant, having been estimated at around £1 billion per year (Liu and Harper, 2013).

[9] The introduction of the AIA will of course have affected the average tax rate for both types of firms. As Fullerton (1984) writes, "average effective tax rate are appropriate for measuring cash flows and distributional burdens, while marginal effective tax rates are designed to capture incentives to use new capital" (p. 30) indicating that it is the marginal rate that is relevant here.

protection legislation or tax credits using size thresholds found in Bjuggren (2018), Saez et al. (2019) and Bøler et al. (2015). We define firms' treatment status in our paper by their total capital investment compared to the tax-allowance threshold in the years prior to introduction of AIA, or in the years before any threshold changes. In this way we obtain estimates of the intention to treat effects of the policy on cloud adoption. Recognising that there may be adjustment costs in reaching the desired capital stock for the firm (Chrinko, 1993), in our baseline estimations we define the treatment and the control group according to investment averaged over the two previous years. We examine the robustness of our findings to alternatives, including the average value for the three years as well as the use of single years of data (the second and third lagged values).

Turning to our empirical findings, while not the focus of the paper, we begin by showing that firms experiencing a fall in their marginal cost of investment as a result of the AIA policy increased their investment in total capital, total IT and hardware, as one would expect. In this regard the paper provides further empirical evidence in support of the view that such policies stimulate investment as previously reported by Cummins et al. (1994), House and Shapiro (2008), Zwick and Mahon (2017), Ohrn (2018) and Maffini et al. (2019).[10] We find evidence of substitution away from cloud and big-data technologies, and of strong differences across small and large firms due to the AIA policy. In our initial estimates, where we ignore expected differences across firm size, we find strong evidence that the AIA policy *discouraged* the adoption of cloud, with stronger effects for substitute cloud hardware services rather than software. Furthermore, the AIA also leads to a *lower* likelihood of using big-data analytics. Small firms responded in a more strongly negative way compared to large firms to the AIA. We also find that these negative effects for small firms are present for both hardware and software cloud services, whereas for large firms the effects of the AIA are confined to cloud hardware services.

[10] Our data do not allow us to measure financial constraints at the level of the firm and so we do not consider whether the effects of this policy were stronger on more or less constrained firms. They also do not allow us to measure precisely firms' marginal tax rates as in Maffini et al. (2019).

We also extend the analysis to explore short- versus longer-run outcomes, from which we find further differences. For large firms, we find short-run but no longer run effects on their cloud adoption decisions, but for small firms the effects occur over both the short- and longer-run. Of interest, for both small and larger firms we find that the effect of the AIA policy on the use of big data by firms were permanently lower. The use of big data analytics by UK firms therefore appears to have been particularly affected by the introduction of this capital incentive programme.

We subject these findings to a number of tests of their robustness including the way that we define treatment and control groups, as well as tests for differences in pre-treatment trends for capital investment (total as well as IT). We also consider placebo tests for cloud adoption at false AIA investment thresholds and the effect of the first year allowance programme studied by Maffini et al. (2019). Finally, we also present in the paper estimates of local average treatment effects on cloud adoption.

In this study we have the advantage of being able to directly compare both traditional IT capital and cloud at the firm-level. As such, this research provides an important contribution to the emerging literature on cloud computing and IT services discussed above (Jin and McElheran, 2017; Bloom and Pierri, 2018; DeStefano, Kneller and Timmis, 2019). While earlier forms of IT have been studied extensively, there is little currently known about the policies that encourage or discourage the diffusion of these technologies. Adoption of earlier waves of IT are shown to be related to IT capital incentives, broadband provision, the competitive environment, the availability of complementary skills, management capabilities or organisational capital and so on (Bloom et al., 2012; DeStefano et al., 2018; Gaggl and Wright, 2017; Haller and Siedschlag, 2011). However, since cloud appears to differ from these earlier technologies in terms of both the way firms access and pay for IT, it is likely that the determinants of cloud also differ.

Research on determinants of cloud computing has largely been confined to the field of information system research (e.g. Schneider and Sunyaev 2016; Oliveira et al 2014; Gupta et al 2013). Yet, the policy environment is likely to be a key driver in the differing diffusion across countries and firms. Adoption across EU28 economies ranges from less than 10% to over 65% of firms in 2016. Across the EU28, the mean adoption of small firms is 26% compared to 56% for large firms (Eurostat, 2018). [11] In one exception, DeStefano, Kneller and Timmis (2019) find that the diffusion high-speed fibre broadband throughout the UK strongly predicts cloud adoption of UK firms, particularly for those with fast expected fibre speeds. This paper contributes to this nascent literature by focusing on another important policy lever - capital investment incentives.

The shift we examine from investments in IT capital towards cloud service expenditures, also connects to the broader literature examining the growing importance to many firms of investments in intangibles (such as innovation, organisational capital, branding etc…) that are also often "off-balance sheet" and difficult to measure. Since the late 1990s, aggregate intangible investment of UK firms exceeds tangible (Borgo et al., 2013) and this is true across the EU14 and the US for the post-crisis period (Corrado et al., 2016). However, in contrast to the highly flexible expenditures on cloud services, intangible investments are characterised by irreversible sunk costs. Accordingly the growing importance of intangibles has been linked with increased advantages of large, productive firms, reflected in trends of growing productivity divergence between leading and laggard firms or increasing industry concentration (Haskel and Westlake, 2017; Crouzet and Eberly, 2019).

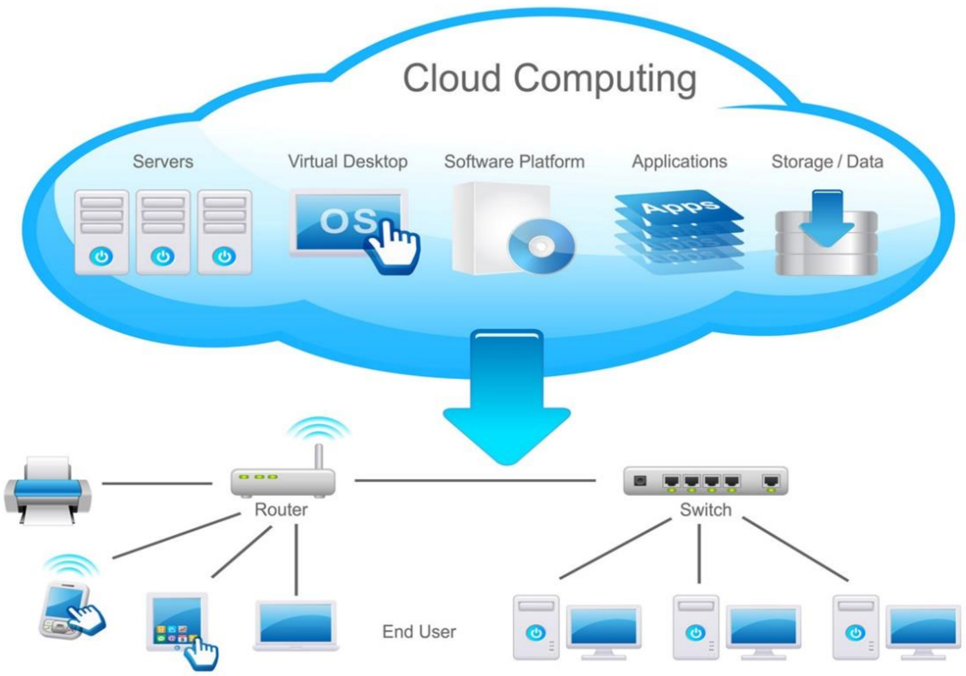
The paper continues as follows: Section 2 provides some discussion on the definition of cloud computing and the perceived benefits of the technology. Section 3 presents more details on the AIA policy, Section 4 describes the data and Section 5 our estimation strategy. Section 6 presents the results, Section 7 presents robustness analyses and Section 8 concludes.

[11] Large firms are defined as those with more than 250 persons employed, small firms are those with 10-49 persons employed. Firms with fewer than 10 persons employed are often not included in the sampling frame for this data.

II.WHAT IS CLOUD COMPUTING

Cloud computing has been called the next generation of IT technology (Hashem et al., 2016). It is a service, delivered by third party providers which "enables ubiquitous, convenient on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (NIST, 2011). Providing a business has reliable high-speed broadband, they can access a range of services including data storage and processing, virtual desktops, software platforms and applications (see Figure 1).

Figure 1: What is cloud computing?



Source: ITPRO (2010)

There are a number of characteristics that distinguish cloud computing from traditional IT services including: economies of scope through online availability of storage and data processing capacities; scalability that is near-infinite; quick deployment; reversibility in the face of uncertainty; flexible pay-as-you-go payment models; and, ease of access through standard devices like desktops, laptops and mobile phones (OECD, 2014; NIST, 2011; Schubert et al., 2010;

Armbrust et al., 2009). Put simply, cloud does not only significantly changes how firms pay for digital technologies, but also changes firms access to them.

One expected benefit of cloud computing is that it lowers entry barriers, leading to new employment opportunities and greater competition, particularly in sectors which previously relied heavily on sunk IT capital (OECD, 2015; Etro, 2009). By shifting IT expenditures from a sunk to a variable cost, this reduces the cost of firms to enter the market – since access to financing is often a particular challenge for young firms with limited credit history. Renting hardware and software on-demand may also enable firms to channel greater investments in essential areas for competitiveness such as R&D and marketing (OECD, 2015; Columbus, 2013). For example, the European Commission (2017) purports that between 2008 and 2020, cloud may result in the creation of 303,000 new businesses and 1.6 million jobs.

Digital platforms facilitated by the cloud, allow firms to scale their operations very quickly without the need for upfront investments, impacting the way they organise. Moreover, by avoiding the necessity to make quasi-irreversible investments in hardware, cloud can allow for greater flexibility and experimentation in the face of uncertainty (Jin and McElheran, 2017). Cloud not only makes the firm itself more flexible, it also allows its employees to be more mobile by decentralising access to data, processing and software to many devices (DeStefano, Kneller and Timmis, 2019).[12]

The use of cloud is often cited as a pre-requisite to other data-driven technologies and innovations such as big-data analytics. Data is an important part of many business models, not just of tech firms, but also retailers, manufacturers, transport, financial services and so on. Estimates suggest the volume of stored data in 2015 exceeded 8 trillion gigabytes, a 60-fold increase on a decade earlier, generated by the proliferation of the internet and

[12] Moreover, since a considerable proportion of server and storage space used by firms is underutilized, greater reliance on the cloud is also expected to improve energy efficiency and lower firm utility costs (Masanet et al., 2014).

interconnected sensors, machines and devices (OECD, 2015). The term “big data” is commonly used to refer to data that are difficult to store, process and analyse through traditional local databases (Hashem et al., 2016). Cloud services are intertwined with big-data, because the volumes of data require flexible storage and processing power that can be scaled up and down, which is often only available via the cloud (McKinsey, 2011).

III.BRIEF DESCRIPTION OF THE CAPTIAL INCENTIVE POLICY

The Annual Investment Allowance (AIA) was introduced in the UK for the financial year 2008-2009, with the objective of stimulating firm invest in new forms of (physical) capital and encourage economic growth (HMRC, 2018). The scheme allowed firms to deduct capital investment during the year, up to the AIA ceiling, from their (pre-tax) profits. As we discuss further below, this ceiling increased a number of times over the course of its implementation. The allowance was not specific to IT capital, but covered all long-term equipment used to produce or sell products – termed “plant and machinery” – which also includes IT capital. This policy was seen as a move away from a size or legal form linked incentive investment schemes, towards a policy targeted at the activity to be encouraged (Crawford and Freedman, 2008).

A *priori* one would expect physical IT capital investment to respond to such capital incentives. Neoclassical investment theory suggests that firms make capital investments in order to adjust to their optimal level of capital, which in turn depends on optimal output and cost of capital. The increase in the AIA threshold lowered the user cost of capital for some businesses, encouraging new investment. Liu and Harper (2013) estimate for example, that following the 2010 increase in the AIA ceiling from £50,000 to £100,000, the user cost of capital for an additional £1 investment between these two figures decreased by 28 percent if financed by retained earnings or equity, and by 31 percent if financed with debt. The authors also note that if internal financing is less costly than external financing, the AIA added positive effects on investment spending for financially constrained firms.

Capital investments also depend of course, on expectations of the future. As already mentioned, during the sample period 2008-2015, the AIA increased a number of times and on one occasion it was briefly lowered (see Table 1). These changes often occurred unexpectedly, and were sometimes announced as being only temporary. Not surprisingly, this approach to tax policy has been much criticised (Miller and Pope, 2015).[13] The AIA scheme was first mentioned in a 2007 budget press notice[14] one year prior to the start of the new allowance and appears to have been unanticipated before that point.[15] The increase to £100,000 was announced in March 2010. A change in government occurred in May, and following a special budget in June 2010, it was announced the AIA ceiling would subsequently be cut to £25,000, effective from April 2012. This new lower threshold was in place for a period of nine months (April 2012 to December 2012), when the government announced in the 2012 Autumn Statement there would be a temporary two-year, ten-fold increase to £250,000 (effective from January 2013).[16] The time period for this 'temporary increase' was later extended to January 2016 and increased further to £500,000 in the 2014 Budget. A further demonstration of the uncertainty over the direction of future changes in this allowance is highlighted by noting that the 2015 election manifesto by the Conservative Party, who went on to form the government, stated that if elected, the supposedly temporary increase it had announced the year earlier would in fact be retained at a permanently higher, but unspecified, level.

As such, the policy changes present an ideal context for the assessment of its impact. The analysis focuses on the four periods in which the AIA increased

[13] Miller and Pope (2015) write 'In an example of how not to design the tax system, the annual investment allowance was decreased and then increased twice for a temporary period.' Pp. 328. Similarly

[14] Budget (2007) – Press Notice 1.

[15] See for example 'Budget 2007: Surprise overhaul announced for capital allowances from 2008' available at https://www.accountingweb.co.uk/tax/hmrc-policy/budget-2007-surprise-overhaul-announced-for-capital-allowances-from-2008

[16] As described in Table 1, for the few part-year changes (e.g. the 9 month allowance of £25,000) we calculate pro-rata allowances over the full financial year. This reflects how the policy was applied, with pro-rata allowances claimed on a firm's total annual investment in the financial year (see https://www.gov.uk/capital-allowances/annual-investment-allowance).

substantially during the sample period, specifically, the years ending in 2009, 2011, 2014 and 2015.[17] To put these numbers in perspective, in 2008 the median value of investment was £562,000. Investment of £50,000 is close to the 19th percentile of the distribution, £100,000 was around the 25th percentile of the distribution in that year, and £250,000 was a little above the 35th percentile.

Table 1: Annual Investment Allowance Ceiling, 2008 to 2015

Financial Year (ending 31st March)	*Annual Allowance Ceiling*
2008 and before	-
2009	£50,000
2010	£50,000
2011	£100,000
2012	£100,000
2013	£81,250*
2014	£250,000
2015	£425,000*

**Pro rata as changed mid-year. The financial year April 2011-March 2012 had 9 months of an allowance of £25,000 and 3 months of £250,000, equal to £81,250 pro-rata for the year. The financial year April 2014 – March 2015 had 9 months of £500,000 allowance and 3 months of £200,000, which equals £425,000 for the year. All other allowances coincide with complete financial years.*
Source: https://www.gov.uk/capital-allowances/annual-investment-allowance

While the introduction and changes to the AIA are expected to influence firm investment decisions, it is important to identify the presence of other policies during our sample period which may bias the results. One potential policy was the First Year Allowance (FYA). The FYA was introduced before our sample period and ceased in 2008, making a reappearance in 2010 for one year. This policy was similar to the AIA in that it provided tax allowances for investments in capital, but were targeted at small firms with revenue below £22.8 million.[18] To ensure that are results are only capturing the effects of the AIA, as a robustness test we later exclude firms in our sample with revenue below this threshold. In terms of digital policies, the UK did have an IT capital specific

[17] We do not consider the small fall in the AIA during the year ending 2013.
[18] See Maffini et al (2019) for further discussions on the FYA.

incentive for small businesses, which was used in Gaggl and Wright (2017), but this was only in place from 1st April 2000 to 31st March 2004, before our sample period.

IV.DATA AND SAMPLE STATISTICS

The research relies on three different types of data: cloud and big-data use by firms; details regarding the introduction and changes to the AIA; and lagged firm investment to identify our set of treated firms. All data are from the Office for National Statistics (ONS), which is the UK Census Bureau equivalent and are measured at the firm-year level.

Information on cloud adoption and use of big-data analytics is available through the E-commerce Survey. The survey was first introduced in the year 2000 and is available annually thereafter. It is a stratified random sample of all firms. The strata are defined by industry and employment, such that larger firms are over-represented. The e-commerce survey contains questions on firms' adoption of each of 7 different types of cloud computing including, hosting the business' databases, processing, the storage of files, email, office software, finance and accounting software and customer relationship management software (CRM). From this data, we construct three aggregates.[19] The first is an overall measure of cloud adoption (of any type) by the firm. The second, we label hardware, which captures hardware services and is defined if the firm purchases cloud for hosting the business' databases, processing and the storage of files. We anticipate that this group are substitutes for physical IT investments. The third group, which we label software, are the remaining categories of email, office software, CRM software and finance and accounting software.[20] We present results for these aggregates as well as the separate types of cloud in the empirical analysis. The questions about cloud adoption are asked in the 2013 and 2015 versions of the E-Commerce survey. In 2008, the year before high-speed fiber

[19] We list these questions in the Appendix.
[20] We also group the various types of cloud technologies using the classification system of the European Commission. Under this definition low-tech cloud is defined as cloud technologies for email, office software and storage of files; medium-tech as cloud for data storage; and high-tech as cloud for finance and accounting software, CRM and own-software.

rollout in the UK and consistent with the assumption of DeStefano Kneller and Timmis (2019), we assume zero cloud adoption for all firms.

The measure of big data is also taken from the 2015 version of the E-commerce survey. Big data is a binary variable which is equal to 1 if an enterprise is analysing big data via either of the following methods: the enterprise's own data collected with smart devices or sensors, data gathered from geolocation data from the use of portable devices, generated from social media, and data collected from other external sources.[21] The E-commerce survey defines big data as typically have characteristics such as: (1) vast amounts of data generated over time, (2) variety in terms of different formats of complex data, either structured or unstructured (for example text, video, images, voice, docs, sensor data, activity logs, click streams, coordinates). (3) velocity in terms of the high speed at which data are generated, become available and change over time. It defines big data analysis as the use of techniques, technologies and software tools for analysing big data from our own business or other data sources. We have further information on whether these big data analytics are conducted in-house, through an external provider, or both.

Details on the Annual Investment Allowance policy over time are provided by UK Tax Authority (HMRC). This data contains information on investment thresholds of the allowance and years in which the policy was introduced and when the thresholds changed. Measures of IT capital investment as well as lagged total investment in plant and machinery – which we use to identify our set of treated firms – are taken from the Annual Business Survey (provided by the ONS). Total investment is recorded for each firm from 1997 and is available annually up to and including 2014 (which is the latest year the ARD is available to researchers). The IT investment data begins in 2008 and is also available up to and including 2014. Finally, data on firm control variables (age, multi-plant status, foreign ownership) are sourced from the UK business registry – the Business Structure Database.

[21] The E-commerce survey include separate questions for each of the different methods of data collection listed above.

Table 2 below provides summary statistics of the main variables.[22] We find 38% of firms in our sample use at least one form of cloud computing services over the sample period. This varies considerably across types of cloud technology. For example, only 8% of firms use cloud for finance and accounting software, but 23% use cloud for storage of files. In terms of big data analytics, on average 21% of firms use big-data over the sample period. 12% of firms conduct big data analytics only in-house, only 2% of firms completely outsource big data analytics to external providers, and 8% conduct a mixture of in-house analytics and through external providers. Note that there are fewer observations on cloud use as information on cloud is only available for the years 2008, 2013 and 2015, and big data for the years 2008 and 2015. The mean value of total investment (log thousands of real UK pounds) within the data is 6.6 (around £700,000). The mean value of investment in IT of 4.4 (around £81,000) and the mean value of investment in IT hardware is 3.8 (£44,000).

Turning to the control variables, 68% of our firms have multiple plants, 28% of firms are foreign owned and the mean (log) age is 3.3. The majority (79%) of firms are in urban areas and 2% are young (under 5 years old).

Table 2: Descriptive statistics

Variable	*Mean*	*Standard deviation*	*Observations*
Cloud (any type)	0.381	0.486	4,678
Cloud Hardware	0.293	0.455	4,678
Cloud Software	0.273	0.446	4,678
Cloud Databases	0.173	0.379	4,678
Cloud Processing	0.110	0.313	4,678
Cloud Storage of files	0.231	0.421	4,678
Cloud CRM	0.126	0.332	4,678
Cloud Finance and Accounting Software	0.078	0.268	4,678
Cloud Office Software	0.128	0.334	4,678
Cloud Email	0.183	0.387	4,678
Cloud Low-Tech	0.092	0.289	4,678
Cloud Med-Tech	0.173	0.379	4,678
Cloud High-Tech	0.211	0.408	4,678

[22] We provide summary statistics for 2015, the year we observe the use of big data by the firm in Appendix Table A1.

Big Data Analytics (any type)	0.211	0.408	2,348
Big Data Analytics – Internal Only	0.119	0.324	2,348
Big Data Analytics – External Only	0.016	0.126	2,348
Big Data Analytics – External and Internal	0.076	0.265	2,348
(log) Total investment	6.561	2.608	28,030
(log) IT acquisitions	4.383	2.253	29,244
(log) Hardware acquisitions	3.812	2.122	29,244
% PCs per employees	59.878	34.393	13,170
(log) Employment	5.650	1.620	56,649
(log) Sales	10.525	1.962	56,614
(log) Sales per worker	4.863	1.620	56,614
Multi-plant	0.679	0.467	56,676
Number of plants	39.383	266.990	56,676
Foreign owned	0.284	0.451	56,676
(log) Age	3.270	0.469	56,676
Urban	0.785	0.410	56,867
Young (<= 5 years)	0.017	0.130	56,676

Note: All monetary values (such as Total investment, IT acquisitions, Hardware acquisitions, Sales) are in log thousands of UK pounds, deflated to 2010 prices using 2 digit PPI deflators provided by the ONS. We add £1 to each investment monetary value to avoid dropping zero investment observations.

V. ESTIMATION APPROACH

In order to estimate the effects on cloud adoption we use changes in the AIA as a quasi-natural experiment to identify a set of treated firms for whom the marginal incentives to invest in capital have fallen. Our empirical set-up borrows from the literature that examines the firm-level impact of changes in R&D tax incentives or labour market policies. Bjuggren (2018) use the introduction of new employment protection, which differentially applied to firms with more or less than 10 employees, as a natural experiment measure the impact of labour market flexibility on productivity. They capture intention to treat effects by using employment levels in earlier years to determine treatment. Similarly, Saez et al. (2019) use a reduction in Swedish payroll taxes for young workers and exploit initial differences in youth employment at the firm level, to measure the impact on firm growth, employment and wages. While Bøler et al.

(2015) use changes in Norwegian R&D thresholds as a quasi-natural experiment to examine the firm-level impact on R&D and imports of intermediate goods.[23]

To identify the effect of the increases in AIA allowances on the adoption of cloud technologies, we use a difference-in-differences regression. The difference-in-difference between before and after the reform investment of the treated firms relative to the control group can be expressed as follows:

$$y_{it} = \alpha + \beta Z_{it} + FE_i + FE_t + \chi_{it} + \varepsilon_{it}$$

Where the variable y_{it} represents the outcome for adoption of firm i in period t.[24] Z_{it} takes the value one for the treatment group in the post-treatment period and zero otherwise. We include firm and year fixed effects, to control for slow-moving unobserved firm factors and common trends, reflected by FE_i and FE_t respectively. χ_{it} is a vector of control variables including lagged investment, age, multi-plant, foreign ownership, α is a constant term and ε_{it} is an error term.

Following the existing literature, we allocate firms into treatment and control groups based on their investment in time periods prior to the reform. Z_{it} then takes the value one for treated firms in the post-AIA reform period and is zero for these firms prior to the reform and for untreated firms. The estimated coefficient β is therefore the difference-in-difference parameter of interest and it measures the intention to treat effect. Following evidence that capital investments are often lumpy and therefore have a relatively low cross-time persistence (Chrinko, 1993; Maffini et al., 2019) we identify treated firms by the comparing the average value of their total investment in the previous two years to the AIA threshold. To address concerns of anticipation, we examine robustness to the use of averages measured across the previous three-years, as

[23] Other papers in the R&D literature to have used changes in threshold ceilings to estimate the impact of tax credits on firm R&D investment (e.g. Bronzini and Piselli 2016; Duguet, 2012; Haegeland and Moen, 2007).

[24] This paper does not consider capital stock because data on hardware and software investments start in 2008 and therefore lack historical information to construction stock measures. In addition, investments are likely to be more responsive to the policy than stocks.

well as using only a single year two or three years previously. We explore the issue of anticipation effects in Section 6 of the paper.

The treated firms, those for whom the marginal incentive to invest has been altered, differ according to the AIA period under study. For the introduction of the AIA, treated firms are those whose (prior average) capital investment would place them below the threshold of £50,000 (19th percentile for total investment). For these firms, their marginal cost of IT capital investment falls as a result of the AIA allowance increased. Since each additional £1 of investment can be deducted from their pre-tax profits, the marginal cost of investment falls by the corporate tax rate. Control firms are those whose marginal cost of investment would be unchanged, in this firms with investment above the threshold. For the 2011 reform, where the threshold was moved to £100,000 (25th percentile for total investment), treated firms are those firms whose (prior average) investment lies between £50,000 and £100,000.[25] The marginal cost of investment for those firms for whom investment is below £50,000, or above £100,000 will be unaffected. Similarly, for the 2014 reform, it is those firms whose (prior average) investment is between £100,000 and £250,000 (35th percentile for total investment) that are treated by the change to the AIA.

We note three points about our empirical setting. Firstly, identification of the effects of AIA on cloud adoption relies on the standard assumption that the treated and non-treated firms have common trends – that is to say, cloud diffusion would grow similarly in treated and non-treated firms, in the absence of the AIA change. One approach to assess this is by examining pre-treatment trends across these two groups. However, our empirical setting is one of the adoption of a newly invented technology, cloud technologies were unavailable in the UK before the rollout of fibre technologies in 2008, such that the adoption by treatment and control firms is zero before this year. To put this differently, common pre-treatment trends holds with certainty for this technology. Instead,

[25] To make this clear a firm with an average investment of £75,000 across 2009 and 2010, would be above the AIA ceiling in 2010 (of £50,000), but in 2011 this firm's prior year investment would be beneath the threshold of £100,000. As we explain in the next section in our data, cloud adoption is binary while investments are represented as continuous variables.

we test for pre-treatment trends for capital investment, including forms of IT capital investment. We report these tests in Section VII. A constraint here is that the IT hardware and software investment data begins in 2008, just one year before the initial introduction of the AIA policy, and ends in 2014.

Second, as we explain in the previous section of the paper, we observe firms' adoption of cloud technologies in three years, 2008, 2013 and 2015. It follows, that the period over which treatment occurs differs according to the AIA reform under consideration. For example, for the introduction of the AIA policy we observe cloud adoption by treated and control firms between 5 and 7 years later, whereas for the 2011 reform we observe outcomes 2 and 4 years later. Therefore, when pooling the AIA reforms into a single regression we capture a mix of immediate, short- and medium-run outcomes. We return to this point in Section VI where we present results for each AIA separately.

Finally, as noted above we estimate "intention to treat" or reduced form estimates of our instrument – using lagged firm investment to identify which firms experience a fall in their marginal cost of investment. To estimate local average treatment effects of the AIA for compliers we use lagged investment to predict current investment levels. We return to this point in Section VII.

VI. EMPRICAL RESULTS

Physical IT Investment

Before presenting the results for cloud and big data adoption which are the focus of the paper, we begin by demonstrating that the AIA had the expected effect of increasing capital investments, including of IT capital, among affected UK firms. In Table 3 we report these for total investment (regression 1), IT capital (regression 2) and IT hardware (regression 3). Hardware forms part of IT capital and IT capital is in turn a component of total investment.

Consistent with evidence of similar types of capital inventive policies in Cummins et al. (1994), House and Shapiro (2008), Zwick and Mahon (2017), Ohrn (2018) and Maffini et al. (2019), within Table 3 we find that the AIA incentivises firms to invest in capital by decreasing the user cost of capital and/or by relaxing financial constraints.[26] The estimated coefficients are reasonably large. The impact of the policy on treated firms leads to an increase in total investment, IT acquisition and hardware acquisition by 109%, 51% and 46% respectively.[27] While the proportional change is substantial, these are not implausibly large changes. The introduction of AIA allowed firms to offset capital investment up to £50,000 against profits. In 2008, this value of investment was at the 19th percentile of the distribution, suggesting that these are reasonably small firms. Secondly, these effects are average over the post-treatment period and therefore are not necessarily realised in a single year (as shown in the figures of the treatment effect over time in Section VII).

Table 3: Capital Allowances and Investment in Capital

Regression No.	*(1)*	*(2)*	*(3)*
Variables	*Total Investment*	*IT Acquisitions*	*Hardware Acquisitions*
AIA treatment	0.737*** (0.084)	0.415*** (0.056)	0.380*** (0.051)
Observations	31,137	32,363	32,363

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. Total investment, IT Acquisitions and Hardware Acquisitions are log values. Sample size is lower for regression 1 due to a few firms with negative investment being dropped. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Cloud Diffusion

The policy levers applied to induce investment in digital technologies have been designed by policy-makers with traditional physical IT capital in mind. These policies may unintentionally create a disincentive to adopt digital services, such

[26] Our data are not well suited to disentangling which of these mechanisms dominates, nor whether there are others, and given our interests lie elsewhere we refrain from making such judgements.

[27] Since the investment outcomes are in logs, the percentage increase in total investment, IT acquisition and hardware acquisition are calculated as 109% = exp(0.737) – 1, 51% = exp(0.415) – 1 and 46% = exp(0.380) – 1 respectively. Again, or data are not well suited to drawing inferences about implied elasticities.

as cloud. This is what we find in our data. Alongside encouraging firms to invest in physical capital investment including in IT capital, it appears that the AIA also led to a *reduction* in the likelihood treated firms adopting cloud technologies.[28] In regression 1 in Table 4, where cloud is defined in its broadest way and includes all cloud services, the evidence suggests that the AIA policy resulted in a *reduction* in the propensity to adopt cloud by 12%. The magnitude of the estimated coefficient is relatively large, since the mean cloud adoption in our sample is 38%. These results reinforce the idea that firms view IT capital investment and purchases of cloud IT services as substitutes – a reduction in the relative price of IT capital leads to a substitution away from cloud and towards IT capital.

We take advantage of detail available within the UK data on the different types of cloud to explore the effect on various forms of this technology that are more likely to substitute for physical IT technologies. Within Table 4 we begin by separating the aggregate measure of cloud (regression 1) into cloud hardware (regression 2), and its subcomponents: businesses databases (regression 3), files (regression 4) and data processing (regression 5). We find the AIA capital incentive is strongly correlated with the adoption of cloud hardware services. Firms treated by the AIA are around 7% *less* likely to adopt hardware forms of cloud compared to the control group. In particular, we find the AIA discouraged adoption of cloud storage (regression 3) and processing (regression 5). A negative effect from the AIA policy is also found on using cloud to host the firms' databases (regression 4), although this is not statistically significant at conventional levels.

As suggested by the summary statistics on cloud adoption, firms often purchase multiple forms of cloud services. This opens the possibility that the firms induced to invest in physical IT because of the AIA policy are also less likely to use other forms of cloud technologies. We explore this in the remaining columns in Table 4 reporting the effects of the AIA policy on the use of any type of cloud

[28] Differences in the sample size between regressions on cloud adoption and investments is because the cloud data comes from the e-commerce survey which is a stratified random sample of the business registry.

software (regression 6) and then separately their use of CRM, finance and accounting, office and email software (regressions 7-10).

In contrast to the effects on the adoption of forms of cloud hardware, we find no evidence for any effect on cloud software services, either measured in an aggregate form (regression 6), or by its components (regressions 7-10).[29] We also note that the coefficient estimates and standard for these software variables are both small, indicating that these zero effects are estimated with a reasonable degree of precision.

[29] In Table A2 in the Appendix we report results for the European Commission definition of low-, medium- and high-tech types of cloud. Overall, we find that the capital incentive allowance is negatively linked to the adoption of the low cloud technologies but not with the more advanced forms of cloud. This perhaps reflects the technological sophistication of the small firms that are treated by the AIA policy.

Table 4: Capital Allowances and Cloud Diffusion

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Variables	*Cloud*	*Cloud Hardware*	*Cloud Storage of files*	*Cloud Databases*	*Cloud Processing*	*Cloud Software*	*Cloud CRM*	*Cloud Finance & Accounting software*	*Cloud Office Software*	*Cloud Email*
AIA treatment	-0.111***	-0.073**	-0.086***	-0.042	-0.037*	-0.043	-0.014	0.004	-0.021	-0.033
	(0.031)	(0.030)	(0.028)	(0.027)	(0.021)	(0.031)	(0.024)	(0.021)	(0.025)	(0.029)
Observations	12,642	12,642	12,642	12,642	12,642	12,642	12,642	12,642	12,642	12,642

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. Each cloud measure reflects a binary variable. Regression 1 reflects adoption of any cloud type. Cloud hardware reflects adoption of either cloud storage of files, databases or processing. Cloud software reflects adoption of either customer relationship management (CRM), finance and accounting, office or email software. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Big Data Analytics

Cloud services are often cited as being intertwined with big-data, because the volumes of data require large amounts of storage and processing power.[30] Cloud offers the opportunity for the firm to access vast storage and processing capability more flexibly than installing the physical server infrastructure themselves and at lower cost (McKinsey, 2011).[31] This opens the possibility that capital investment policies in the UK may also act to slow the diffusion of big data analytics across firms. We find evidence in support of this view. The AIA threshold reduces the use of big data analytics of UK firms by around 15% (regression 1 in Table 5).

In the remaining regressions in Table 5 we disentangle big data adoption further by considering whether the analytics are conducted internally within the firm, or through external data analytics providers or both. On the one hand, since cloud computing is inherently available through external providers, one may imagine that the AIA impacts the propensity to use external suppliers to analyse big data. On the other hand, it is well-established that investment in IT requires complementary internal investments to leverage their full potential, which combined with privacy concerns, may imply AIA impacts internal big data analytics within the firm. We find that the AIA policy did not lead to a decrease in the propensity to analysis big data only externally or only internally – with estimated coefficients very close to zero (see regressions 2 and 3 in Table 5). However, there is a large negative effect on the firms simultaneously engaging external firms along with undertaking analytics in-house (regression 4). We find the AIA policy led to a 10% decrease in the likelihood of analysing big data both internally and through external providers.

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[30] We use Table A3 in the Appendix to show there is a significant positive correlation between cloud use and big data.

[31] As is often quoted in the IT systems literature. The cost of purchasing 1 server for 100 hours from a cloud provider, is the same as the cost of purchasing 100 servers for 1 hour.

Table 5: Capital Allowances and Big Data Analytics

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*
Variables	*Big Data Analytics*	*Internal-Only Big Data Analytics*	*External-Only Big Data Analytics*	*External & Internal Big Data Analytics*
AIA treatment	-0.149***	-0.046	-0.005	-0.098***
	(0.037)	(0.032)	(0.014)	(0.022)
Observations	10,521	10,521	10,521	10,521

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. The cloud and big-data analytics measures reflect a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Treatment Heterogeneity

The IT literature studying the effects of cloud on the performance of firms strongly suggests a difference between outcomes for small and larger firms. The change in the nature of IT costs from a fixed to a variable cost, it has been argued, has enabled new business models allowing young firms to scale operations quickly without the need for acquiring a mass of IT assets or labour. This has typically been labelled ‘scale without mass’. Up-front investments associated with IT can be burdensome for young firms, given their financial constraints due to their lack of credit history, demand uncertainty and the intangible nature of any intellectual capital. Cloud is suited to the digital needs of small firms and is found to increase their scale and productivity (DeStefano Kneller and Timmis, 2019). This echoes a finding within the literature capital incentives which suggests that such policies act particularly strongly on firms that are credit constrained, who are typically also likely to be small. Cummins et al. (1996), Hassett and Hubbard (2002) and Gorodnichenko and Schnitzer (2013) find that constrained firm respond strongly to changes in the user cost of capital.

In this section we allow for heterogeneity in the effects of the AIA policy across small and large firms, where we categorise small firms as those with employment below 250 employees in 2008.[32] We report the results from this exercise in Table 6, for the aggregate measure of cloud (regression 1), cloud hardware and software separately (regressions 2 and 3) and the two measures of big data found to be relevant in Section VI (regressions 4 and 5). In Appendix Table A4 we report the results for the seven different forms of cloud available in the data separately.

We find evidence of treatment heterogeneity, with in general stronger effects on small compared to large firms. For all the measures of cloud we find that small firms respond more strongly to the AIA policy compared to large firms. The AIA policy caused both small and large firms to become significantly less likely to adopt cloud technologies, although for large firms this appears to be explained by a reduced likelihood of using cloud for data storage. For small firms we find that there are also effects for other types of hardware (In Table A4 we also find effect for the storage of files, databases and processing). In addition, in regression 3 we now find evidence that the AIA capital incentive programme also affected the adoption of various forms of cloud software (and in Table A4 that this holds irrespective of the various forms of software in the data). The effect on small firms are particularly strong. In regression 1 in Table 6 the estimates suggest that small firms for whom the AIA makes capital investment less costly, are 36% less likely to adopt cloud technologies. They are 26% less likely to adopt hardware forms of cloud and 31% less likely to adopt software. The latter result is of interest as it indicates complementarity between different forms of cloud for small firms, whereas this is less obvious for large firms.

The effects for the general type of big data analytics in regression 4 are similar to the aggregate measure of cloud and for data. We find that both small and large firms are affected by the AIA policy, and that the effect is stronger for small compared to large firms. For the use of big data using a combination of internal and external support (regression 5) the results are modified somewhat. For this type of big data analytics we find that both small and large firms treated by the

[32] Defined in this way there are 2,058 firm-year observations on small firms and 10,584 firm-year observations on large firms. We have tried other similar thresholds with quantitatively similar results.

AIA capital incentive are less likely to use this form of big data analytics, and that the estimated effects is similar in size for both of these groups of firms such that the interaction with the small firm dummy is not statistically significant.

Table 6: Treatment Heterogeneity

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Variables	*Cloud*	*Cloud Hardware*	*Cloud Software*	*Big Data Analytics*	*Big Data internal & external*
AIA treatment	-0.078**	-0.050	-0.011	-0.131***	-0.099***
	(0.032)	(0.031)	(0.032)	(0.039)	(0.023)
AIA treatment	-0.370***	-0.259***	-0.356**	-0.226***	0.007
* Small Firms	(0.080)	(0.090)	(0.072)	(0.081)	(0.074)
Observations	12,642	12,642	12,642	10,521	10,521

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. Each cloud measure reflects a binary variable. Cloud hardware reflects adoption of either cloud storage of files, databases or processing. Cloud software reflects adoption of either customer relationship management (CRM), finance and accounting, office or email software. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Short- Versus Medium-Run Outcomes to Adoption

Within the empirical analysis conducted so far, we have assumed that the effects of treatment are the same across time. In practice, we observe the use of cloud technologies at three separate points in time (2008, 2013 and 2015) such that the effects of changes in the AIA policy are measured a varying number of years later. In Table 7 we consider separately the changes in the AIA threshold in 2009, 2011 and 2014.[33] Given the results in the previous section we allow this effect to differ for small and large firms.

Within Table 7 we continue to find that the AIA tax policy led to a reduced likelihood that the firm adopts cloud computing for small firms, where this effect is statistically significant for all of the reform years. This would tend to suggest that the effect of the AIA capital incentive may permanently delay the adoption of substitute technologies such as cloud.[34] These results are similar when we separate out cloud hardware and software. For large firms we find these results differ somewhat. For these firms we find that the 2009 and 2011 reforms had no significant effect, whereas the effect of the 2014 reform on cloud adoption is statistically significant. This would may suggest that the effect of the capital incentive policy for large firms is to delay adoption, but not permanently so. For software we find no significant effects from any reform year, whereas the results for cloud hardware mirror those for the aggregate variable.

For the adoption of big data we find strong effects from all of the waves of the AIA and fewer differences across small and large firms (either the general measure of whether it is done using a combination of internal and externally). This would appear to indicate that while the AIA policy delayed rather than permanently prevented the adoption of cloud technologies, the lack of

[33] We use Table A5 in the Appendix to describe the effects on investment of the various AIA waves.

[34] One potential concern may be that the results here are driven by certain sectors. Robustness tests exploring heterogeneity in the effects of the policy find no evidence of this.

experience of using cloud technologies may have had more permanent impacts of complementary technologies such as big data analytics.

Table 7: Capital Allowances Over Time

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Variables	*Cloud*	*Cloud Hardware*	*Cloud Software*	*Big Data Analytics*	*Big Data Internal & External*
AIA 2009	-0.031	-0.010	0.030	-0.121**	-0.079**
	(0.040)	(0.039)	(0.040)	(0.049)	(0.032)
AIA 2009*small firms	-0.331***	-0.273***	-0.351***	-0.147	-0.089***
	(0.106)	(0.099)	(0.069)	(0.168)	(0.162)
AIA 2011	-0.186**	-0.085	-0.117	-0.108	-0.169***
	(0.091)	(0.090)	(0.081)	(0.105)	(0.013)
AIA 2011*small firms	-0.466***	-0.407***	-0.362***	-0.275***	0.011
	(0.095)	(0.095)	(0.088)	(0.114)	(0.020)
AIA 2014	-0.130**	-0.128**	-0.046	-0.164**	-0.107***
	(0.056)	(0.053)	(0.060)	(0.066)	(0.035)
AIA 2014*small firms	-0.373**	-0.131	-0.346	-0.287***	-0.067**
	(0.171)	(0.240)	(0.212)	(0.065)	(0.033)
Observations	12,293	12,293	12,293	10, 295	10,295

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. Each cloud measure reflects a binary variable. Cloud hardware reflects adoption of either cloud storage of files, databases or processing. Cloud software reflects adoption of either customer relationship management (CRM), finance and accounting, office or email software. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

VII. ROBUSTNESS ANALYSES

In this section we conduct a number of robustness analyses of the earlier baseline results. We begin by considering the robustness to alternative ways of determining treated firms. We then examine a placebo test, where a false AIA threshold is used to test for effects amongst the control group of firms that may invalidate our approach. Next we present estimates of local average treatment effects before finishing by considering an alternative tax incentive in the UK, the First Year Allowance, which may be confounding the prior estimates.

Alternative Treatment Groups and Placebo Tests

In regressions 1, 2 and 3 of Table 8 we establish the robustness of the findings to alternative methods of determining treated firms. In the earlier baseline estimation we used the average of firms' investment over the previous two years to determine their inclusion in either the treatment or control group. We offer three alternatives in the table. We begin by using the average of firms' investment over the previous three years to determine their treatment status (regression 1).[35] In regressions 2 and 3 we use the value of their lagged investment in the period t-2 and t-3 respectively. An advantage of the use of lags is that it reduces the likelihood that our results are driven by anticipation effects. However, since investment is inherently lumpy, it introduces some additional noise.

As reported in regressions 1 to 3, we find that this change in the way that we determine treated firms reduces the magnitude of the estimated treatment effects, but not the pattern of the findings. The intention to treat effects suggest that raising the AIA thresholds decreased cloud adoption by around 7% in regressions 1 and 3 and by 12% in regression 2.

[35] Note that differences in the sample size between 2 year lags and 3 year lags are driven by the fact that the data is an unbalanced panel and thus firms which did not exist in the sample three years vs two years ago are not included in the regressions.

Table 8: Alternative Treatment Groups

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Variables	*Cloud*	*Cloud*	*Cloud*	*Cloud*	*Cloud*
Treatment group	*Averages based on 3 year lags*	*2 year lag*	*3 year lag*	*Placebo treatment (100K-150K in 2009)*	*Placebo treatment (150K-200K in 2009)*
AIA treatment	-0.070**	-0.115***	-0.065**	-0.075	-0.084
	(0.033)	(0.028)	(0.029)	(0.084)	(0.086)
Observations	12,444	12,642	12,444	6,496	6,496

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions 4 and 5 use the average of previous 2 years firm investment to determine the treatment group (as in the baseline estimation) to determine the placebo treatment group. Cloud reflects a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

As already noted in Section V when describing our empirical methodology, our key identifying assumption is that firms have a common trend, in the absence of changes in the AIA policy. We also noted that as we study the adoption of a new technology common pre-trends holds by design for cloud adoption. To provide support for this assumption we instead use an indirect test, examining the effects of a placebo change in the AIA threshold. We measure a placebo increase in the AIA threshold from £100,000 to £150,000 in 2009 (rather than zero to £50,000 as in reality) in regression 4 and a placebo increase in the AIA threshold from £150,000 to £200,000 in regression 5.[36] For these placebo firms, their marginal cost of investment did not change in reality and therefore we should observe no difference in their cloud adoption compared to the control group. To generate the control group we compare these placebo firms against firms who also faced no change in the marginal cost of capital (i.e. we only exclude firms that were genuinely treated by the 2009 AIA introduction). The placebo treatment is then estimated equivalently to the earlier baseline estimates.

Comfortingly, we find these placebo changes in the AIA allowance is associated with no significant change in cloud adoption (see Table 8). The estimated coefficients are close to zero for each outcome. This would tend to rule out the presence of confounding factors that explain the previous findings and suggest those firms just above the true threshold (with lagged investment between £100,000 and £150,000 or between £150,000 and £200,000), have similar trends to other firms in the control group.

Local Average Treatment Effects for IT investment decisions

The results thus far have presented so-called "intention to treat" or reduced form estimates of our instrument – using lagged firm investment to identify which firms experience a fall in their marginal cost of investment. Recall, we use lagged investment out of a concern that anticipation effects of the policy may

[36] In Table A6 in the Appendix we show that the effect on capital investment, including forms of IT capital, are also statistically insignificant in these regressions. We show this for £100K-£150K placebo. The results are similar for the £150K-£200K placebo test and are available on request from the authors.

lead to some firms deferring investment decisions. However, lagged investment is not a perfect predictor of current investment. For instance, some firms may grow rapidly in the intervening years and their investment exceed the AIA thresholds in the current period. To address this point, we use the set of firms using lagged investment (the treatment group defined earlier), to predict a new set of treated firms defined using their current investment – estimating a local average treatment effect. That is to say, we estimate the treatment effect of the AIA for compliers - those who experience a reduction in their marginal investment costs at time t because of their average two-year prior investment levels.

In Table 9 we report the 2SLS estimates of cloud adoption on AIA, for hardware and software cloud services, respectively. In the first stage, we find that using lagged investment is a strong predictor of a reduction in investment costs in the current period, with an F-statistic exceeding 123. However, the estimated coefficient is relatively small (around 0.355), suggesting that there is reasonable year-on-year noise in investment values. This likely reflects the inherent lumpiness investment decisions, which for smaller firms (the treatment group of the AIA policy) can mean years of zero investment. In the second stage we find broadly similar results to the earlier reduced form estimates. Reductions in marginal cost of investment significantly reduce the likelihood of cloud adoption, and this is evident through the use of cloud hardware services rather than cloud software services.[37]

We find larger second stage coefficients than the earlier reduced form estimates, for example, the AIA leads to a 31% reduction in the likelihood of cloud adoption. The estimates suggest that compliers have a larger estimated treatment effect – that is to say AIA impacts cloud adoption more for those with relatively stable (and small) levels of investment (compared to say, rapidly growing or declining firms). This is consistent with a narrative that those firms whose investment increases above AIA threshold between t-2 and t are generally

[37] We continue to find no effect on the adoption of the disaggregated types of cloud. We include these results in Appendix Table A7 for completeness.

growing rapidly and so may be more likely to invest in cloud anyway – without the investment incentive.

Table 9: Local Average Treatment Effects of the AIA on Cloud Adoption

Regression No.	*(1)*	*(2)*	*(3)*
Second Stage:	*Cloud*	*Cloud Hardware*	*Cloud Software*
AIA treatment	-0.312***	-0.207**	-0.121
	(0.091)	(0.086)	(0.088)
First stage:			
AIA treatment – lagged investment	0.355***	0.355***	0.355***
	(0.032)	(0.032)	(0.032)
Observations	4,675	4,675	4,675
Cragg-Donald F-statistic	521.13	521.13	521.13
Kleibergen-Paap F-statistic	123.58	123.58	123.58

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. "AIA treatment – lagged investment" is constructed using firms' 2 year average lagged investment (consistent with earlier tables) to determine the set of firms with a fall in their marginal cost of investment. "AIA treatment – current investment" is constructed similarly, but using firm investment in the current period to determine the set of firms. Each cloud measure reflects a binary variable. Cloud hardware reflects adoption of either cloud storage of files, databases or processing. Cloud software reflects adoption of either customer relationship management (CRM), finance and accounting, office or email software. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Graphs of the Treatment Effect over Time

In this section we examine separately the 2009 introduction, and the increase of the allowance in 2011. For each change, we regress total investment on year and year-treatment dummies. We have normalised the year in the graphs to be relative to the treatment year, such that time zero is the year of the AIA change, time -1 is the year before the change, time +1 is the year after and so on. The regressions corresponding to each graph are reported underneath each graph. The plotted coefficients relate to the year-treatment dummies and their associated confidence intervals.

The objectives of these figures are twofold. Firstly, they illustrate how long it takes for changes in the capital allowance to materialise into changes in the investment decisions of treated firms. Maffini et al (2019) show that earlier tax incentives often take several years to translate into changes in investment decisions. Secondly, by also examining changes to the allowance in 2011, it allows one to assess whether there was any anticipation effect to the policy and thus test the robustness of these policy measures within an empirical framework.[38] As noted earlier, pre-AIA trends for cloud computing are zero by construction, so are not reported here.

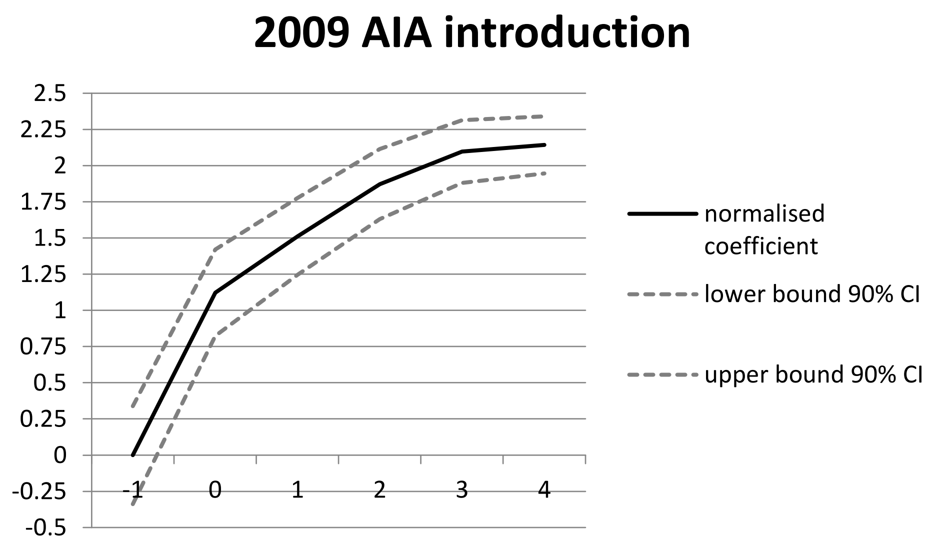
Figures 3 to 7 demonstrate a positive relationship for the introduction of the AIA in 2009 for the treated firms on their total and different forms of IT capital investments. Two aspects of the results are of interest. Firstly, the results indicate that there is not significant difference in investment between treated and control firms in the year prior to the introduction of the AIA policy. Secondly, in the post-treatment time period the effect of the policy on treated firms takes some time to materialise. The effect of treatment differs according to the type of capital over time, although by the final period there is a statistically significant increase for all forms of investment from the policy. For total investment the effect of the AIA allowances continues to grow for three years

[38] The data sample for the UK begins in 2008 and it is therefore not possible to examine potential anticipation effects of the policy more than one year before the AIA was introduced.

before flattening off. For IT and hardware treatment the effects appear to be realised somewhat faster, perhaps because faster depreciation rates imply more frequent replacement decisions. For IT acquisitions the treatment effect appears to be fully realised after two years, but for hardware for it appears to be after one. Not surprisingly, the magnitude of the treatment effect appears larger for total investments than for IT investment given that the allowance applies to capital investments more generally, rather than just IT.

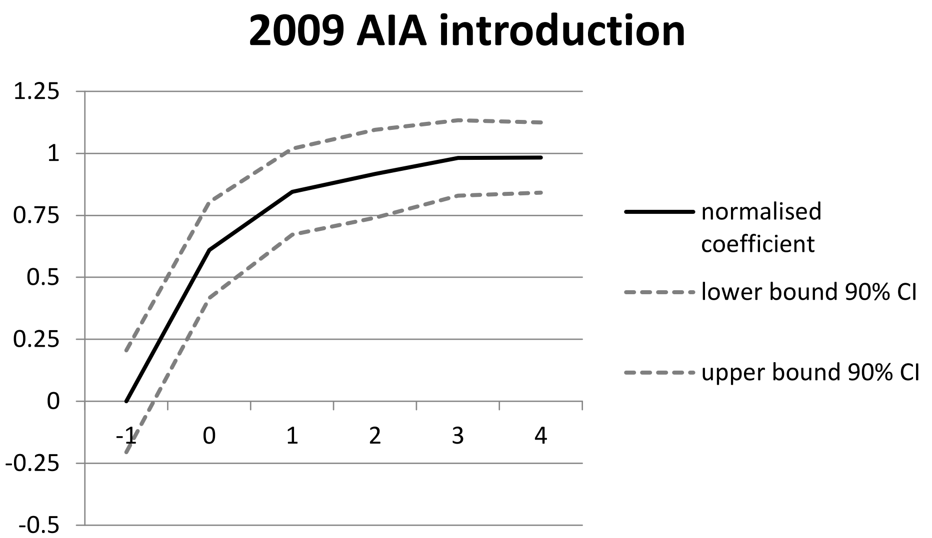
The investment effects of subsequent increase in the AIA in 2011, from £50,000 to £100,000 displays similar results (see Figures 5 to 7). There is a significant increase in total investments, IT and hardware acquisition, despite having fewer post-treatment years in our data. The estimated impacts are smaller than the 2009 AIA introduction, consistent with what we noted earlier in Table 5. Not surprisingly, the years before the 2011 increase are somewhat noisy, as these may include firms who were previously treated in 2009. Importantly however the pre-treatment estimates are not significantly different from zero. This suggests there does not appear to be a different pre-treatment trend in investment between the treatment and control groups, supporting our use of AIA changes as a quasi-natural experiment.

Figure 2: Total Investment, 2009 AIA change



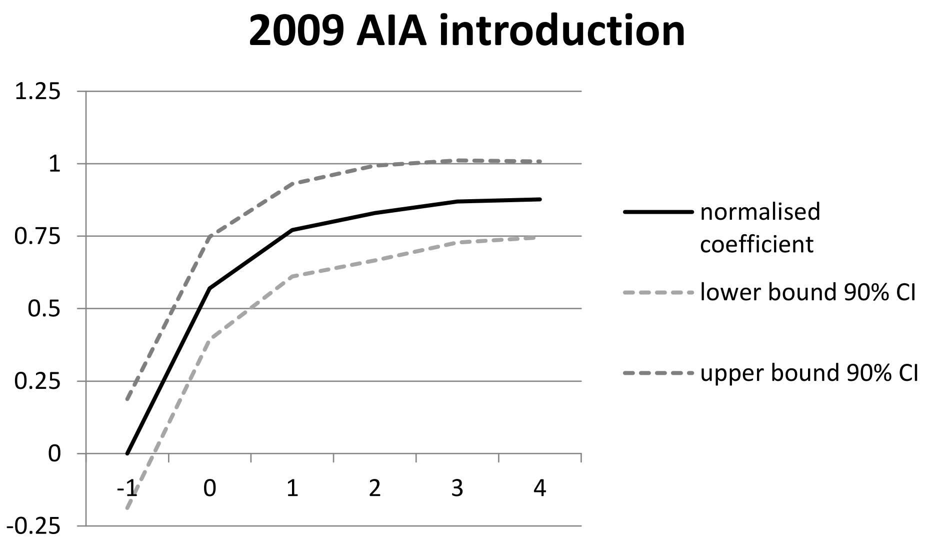
Notes: The figure illustrates the relationship between the introduction of the AIA in 2009 on (log) total investment for the treated firms. The figure is calculated by regressing the total investment on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure 3: IT Acquisition, 2009 AIA change



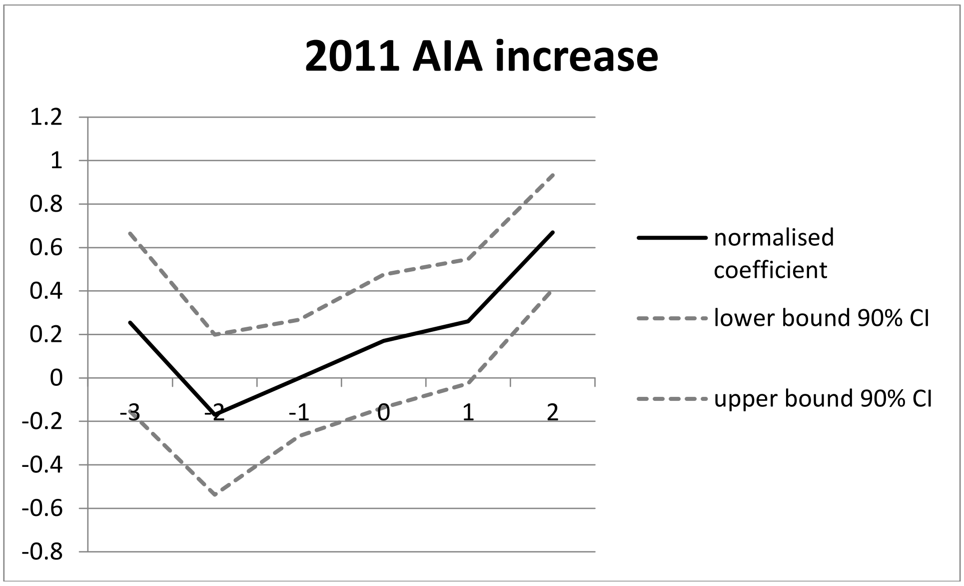
Notes: The figure illustrates the relationship between the introduction of the AIA in 2009 on (log) IT acquisition for the treated firms. The figure is calculated by regressing the IT acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure 4: Hardware Acquisition, 2009 AIA change



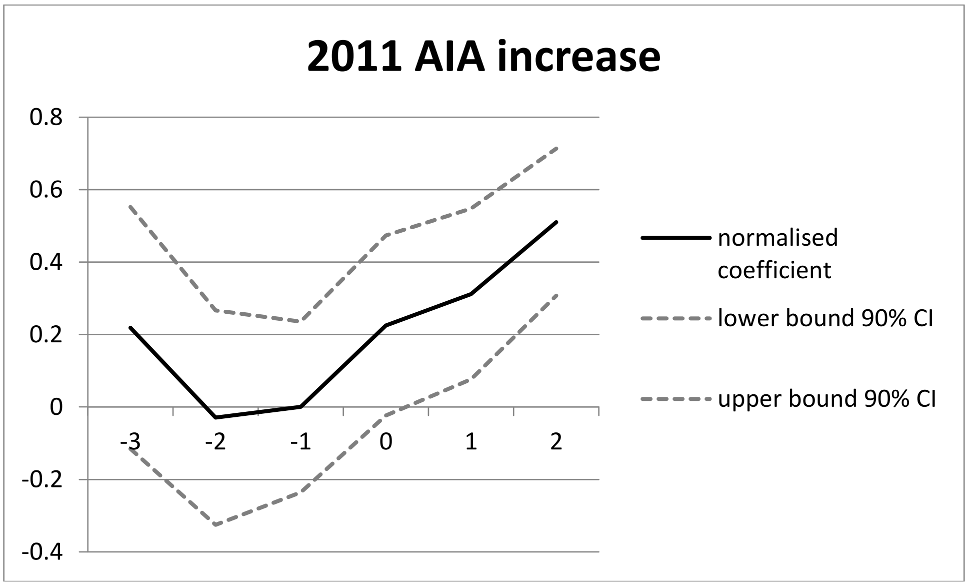
Notes: The figure illustrates the relationship between the introduction of the AIA in 2009 on (log) hardware acquisition for the treated firms. The figure is calculated by regressing the hardware acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure 5: Total Investment, 2011 AIA change



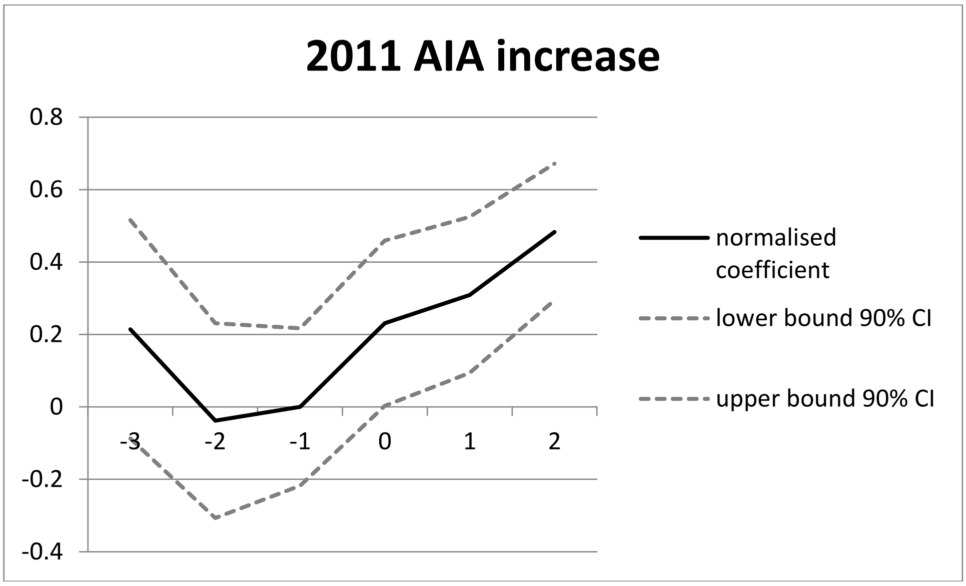
Notes: The figure illustrates the relationship between the change in the AIA in 2011 on (log) total investment for the treated firms. The figure is calculated by regressing the total investment on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure 6: IT Acquisition, 2011 AIA change



Notes: The figure illustrates the relationship between the change in the AIA in 2011 on (log) IT acquisition for the treated firms. The figure is calculated by regressing the IT acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure 7: Hardware Acquisition, 2011 AIA change



Notes: The figure illustrates the relationship between the change in the AIA in 2011 on (log) hardware acquisition for the treated firms. The figure is calculated by regressing the hardware acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Alternative Tax Incentives – First Year Allowance

In the first year of our sample period, 2008 (the year before the AIA introduction) and again for the year 2010, a First Year Allowance (FYA) policy existed in the UK which provided tax allowances to small firms. Firms with sales up to £22.8 million were eligible to receive a tax rebate on capital investments – through accelerated depreciation (Maffini et al., 2019). One concern is that in 2010, we may be conflating the AIA policy with the one-year introduction of the FYA, since the AIA targeted firms with smaller investment and so are likely to be small in terms of sales as well. A second concern is that our estimated treatment effects of AIA introduction in 2009, may be underestimated, since we are also capturing the removal of the FYA from 2008.

In order to examine the robustness of the effects of AIA on firm investment decisions, we exclude firms in our sample that ever have sales of less than £22.8 million in any year during our sample period. This is a conservative approach and results in the loss of more than a tenth of our sample. The regressions in

Table 10 suggests that the results are robust to the exclusion of these firms. The signs, and statistical significance of capital investment, IT investments and cloud are consistent with the baseline results in Tables 3 and 4.

As an additional robustness test, we exclude the largest firms, further from the threshold, out of a concern that our control group includes outliers. In particular, we exclude those making investments of £10 million or more, which represents around 10% of our sample (see Appendix Table A8). Again, the results are consistent with the baseline results in Tables 3 and 4 suggesting our results are not being driven by the presence of outlier firms in our sample.

Table 10: Controlling for First Year Allowances

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*
Variables	*Total Investment*	*IT Acquisitions*	*Hardware Acquisitions*	*Cloud*
AIA treatment	0.787***	0.453***	0.416***	-0.124***
	(0.098)	(0.064)	(0.059)	(0.034)
Observations	27,513	28,589	28,589	11,006

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. Total investment, IT Acquisitions and Hardware Acquisitions are log values, cloud reflects a binary variable. Excludes firms with sales in any period of our sample of less than £22.8 million. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

VIII. CONCLUSIONS

The arrival of cloud computing presents a change for how firms can access IT, but little is known about whether the policy implications drawn from earlier waves of IT can be extrapolated. This paper uses the lens of capital incentives to examine firm decisions to adopt cloud or invest in physical IT, and also how this impacts the diffusion of big-data analytics. We take advantage of the introduction and subsequent changes to a UK tax incentive for physical capital investment – the Annual Investment Allowance (AIA). We find that firms that experienced a fall in their marginal cost of investment, increase their investment in total capital, in addition to IT and hardware, as one would expect. But these firms are significantly *less* likely to adopt cloud. Our results suggest that firms view IT capital investment and cloud adoption as substitutes – a reduction in the price of IT investment leads to a substitution away from cloud and towards traditional IT. Furthermore, the AIA also induced a *lower* likelihood of using big-data analytics.

Our results present a challenge for government policy. Every OECD economy currently has some form of capital incentive policy and many include or even explicitly target IT capital investments (as the UK did before 2005) (Tax Foundation, 2018). Firms in the UK are relatively early adopter of cloud compared to other high-income economies, in part due to the early roll-out of superfast fibre broadband (see DeStefano, Kneller and Timmis, 2019), and therefore offers a possible prognosis for other economies. By incentivising traditional forms of IT, government policy may inadvertently be slowing the diffusion of newer technologies, such as the cloud, that are delivered as online services. While this matters in itself, our results show this is likely to have knock-on effects to further slow the diffusion of other data-driven technologies that leverage the cloud, such as big-data analytics. More generally, our results suggest that policies designed for firms comprised of PCs, servers, bricks and mortar may need reconsideration for businesses models that increasingly comprise of data and other intangibles.

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APPENDIX

Types of cloud in E-commerce survey
Does this business buy any of the following cloud computing services used over the internet

- *Email*: Email, as a cloud computing service
- *Software*: Office software for example word-processing or spreadsheets, as a cloud computing service
- *Databases*: Hosting the business' database(s) , as a cloud computing service
- *Storage of files*: Storage of files , as a cloud computing service
- *Finance Software*: Finance or accounting software applications, as a cloud computing service
- *CRM*: Customer relations management software, as a cloud computing service
- *Own Software*: Computing capacity to the business' own software, as a cloud computing service

Table A1: Sample Statistics for Firms with Big Data Variable (2015 data)

Number of observations	n=5523	n=1648	n=1026	n=152	n=462
Mean Values	None users of Big Data Analytics	Big Data Analytics	Internal-Only Big Data Analytics	External-Only Big Data Analytics	External and Internal Big Data Analytics
Cloud	0.359	0.691	0.656	0.595	0.799
Cloud Hardware	0.266	0.493	0.498	0.500	0.458
Cloud Processing	0.069	0.264	0.236	0.209	0.342
Cloud Storage	0.234	0.500	0.462	0.373	0.626
Cloud Data	0.135	0.357	0.321	0.281	0.462
Cloud Data/Storage	0.258	0.498	0.500	0.497	0.470
Cloud Software	0.280	0.497	0.500	0.502	0.475
Cloud CRM	0.087	0.271	0.238	0.176	0.376
Cloud Finance	0.091	0.186	0.168	0.176	0.229
Cloud Office Software	0.148	0.360	0.316	0.327	0.468
Cloud Email	0.208	0.424	0.398	0.373	0.498
Cloud Low-Tech	0.130	0.355	0.356	0.338	0.359
Cloud Med-Tech	0.135	0.479	0.467	0.451	0.499
Cloud High-Tech	0.166	0.496	0.489	0.487	0.499
% PCs per employees	63.287	75.156	75.206	67.984	77.338
(log) employment	3.593	5.562	5.340	4.835	6.289
(log) sales	7.971	10.355	10.016	9.549	11.369
(log) sales per worker	4.448	4.819	4.715	4.707	5.086
Multiplant	0.316	0.624	0.585	0.569	0.729
Number of plants	16.339	65.404	49.184	28.000	113.468
Foreign owned	0.133	0.279	0.263	0.190	0.346
(log) age	2.870	3.110	3.062	3.158	3.198
Urban	0.748	0.804	0.792	0.796	0.833
Young	0.149	0.097	0.109	0.098	0.071

Notes: The summary statistics above reflect firms with non-missing big data analytics measure in 2015. They show the characteristics of firms that do and do not use big data analytics in 2015.

Table A2 Capital Allowances and Investment in Low, Medium and High Technology Cloud

Regression No.	*(1)*	*(2)*	*(3)*
Variables	Cloud Low-Tech	Cloud Med-Tech	Cloud High-Tech
AIA treatment	-0.035*	-0.042	-0.031
	(0.019)	(0.027)	(0.029)
Observations	12,642	12,642	12,642

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. Each cloud measure reflects a binary variable. Cloud low, medium and high technology follow the European Commission classification. Low-tech cloud is defined as cloud technologies for email, office software and storage of files; medium-tech as cloud for data storage; and high-tech as cloud for finance and accounting software, CRM and own-software. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Table A3: OLS Correlations Cloud and Big Data

Regression No.	*(1)*	*(2)*	*(3)*	(4)
Variables	Big Data Analytics	Internal-Only Big Data Analytics	External-Only Big Data Analytics	External and Internal Big Data Analytics
Cloud	0.183***	0.069***	0.025**	0.089***
	(0.029)	(0.025)	(0.010)	(0.020)
Observations	10,521	10,521	10,521	10,521

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Cloud and big data measures reflect a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Table A4: Treatment Heterogeneity

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Variables	*Cloud Storage*	*Cloud Data*	*Cloud Processing*	*Cloud CRM*	*Cloud Finance and accounting*	*Cloud Office software*	*Cloud Email*
AIA treatment	-0.024	-0.068**	-0.027	0.001	0.013	-0.007	-0.013
	(0.023)	(0.029)	(0.028)	(0.026)	(0.022)	(0.027)	(0.030)
AIA treatment	-0.149***	-0.197**	-0.169**	-0.171***	-0.110*	-0.163***	-0.229***
* Small Firms	(0.024)	(0.082)	(0.070)	(0.063)	(0.062)	(0.043)	(0.072)
Observations	12,642	12,642	12,642	12,642	12,642	12,642	12,642

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. Each cloud measure reflects a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Table A5: Individual Changes of Capital Allowances and Investment in IT Capital vs Cloud Adoption

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*
Variables	Total Investment	IT Acquisition	Hardware Acquisition	Cloud
AIA treatment 09	1.690***	0.845***	0.765***	-0.058
	(0.152)	(0.089)	(0.080)	(0.039)
AIA treatment 11	0.194	0.252**	0.251***	-0.235***
	(0.131)	(0.101)	(0.091)	(0.085)
AIA treatment 14	-0.017	-0.140	-0.131	-0.166***
	(0.111)	(0.086)	(0.080)	(0.055)
Observations	30,337	31,554	31,554	12,293

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. The estimated treatment effects for each treatment group are shown individually, for the introduction of the AIA in 2009 and increases in 2011 and 2014. Therefore each cell represents the estimate from a separate regression. Total investment, IT Acquisitions and Hardware Acquisitions are log values, cloud reflects a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Table A6: Placebo test of artificial AIA Changes on IT investment decisions

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*
Variables	Total Investment	IT Acquisitions	Hardware Acquisitions	Cloud
	Placebo treatment (100K-150K in 2009)			
AIA treatment	0.061	0.103	0.128	-0.075
	(0.169)	(0.115)	(0.108)	(0.084)
Observations	20,086	20,905	20,905	6,496

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the placebo treatment group. Total investment, IT Acquisitions and Hardware Acquisitions are log values, cloud reflects a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Table A7: Local Average Treatment Effects of the AIA on Cloud Adoption

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Second Stage	*Cloud Storage*	*Cloud Data*	*Cloud Processing*	*Cloud CRM*	*Cloud Finance*	*Cloud Office Software*	*Cloud Email*
AIA treatment	-0.241***	-0.119	-0.105*	-0.040	0.010	-0.060	-0.094
	(0.082)	(0.076)	(0.060)	(0.069)	(0.060)	(0.070)	(0.082)
First stage:							
AIA treatment – lagged investment	0.355***	0.355***	0.355***	0.355***	0.355***	0.355***	0.355***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Observations	4,675	4,675	4,675	4,675	4,675	4,675	4,675
Cragg-Donald F-statistic	521.13	521.13	521.13	521.13	521.13	521.13	521.13
Kleibergen-Paap F-statistic	123.58	123.58	123.58	123.58	123.58	123.58	123.58

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. "AIA treatment – lagged investment" is constructed using firms' 2 year average lagged investment (consistent with earlier tables) to determine the set of firms with a fall in their marginal cost of investment. "AIA treatment – current investment" is constructed similarly, but using firm investment in the current period to determine the set of firms. Each cloud measure reflects a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Table A8: Capital Allowances and Investment in IT Capital vs Cloud Adoption, excluding larger investors

Regression No.	(1)	(2)	(3)	(4)
Variables	Total Investment	IT Acquisitions	Hardware Acquisitions	Cloud
AIA treatment	0.678***	0.390***	0.358***	-0.105***
	(0.083)	(0.056)	(0.051)	(0.033)
Observations	27696	28917	28917	11480

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Regressions 1 to 4 use the average of 2 year lagged firm investment. Excludes firms with investment exceeding £10million. Total investment, IT Acquisitions and Hardware Acquisitions are log values, cloud reflects a binary variable. Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*