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Capital incentives in the age of intangibles

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GEP

CAPITAL INCENTIVES IN THE AGE OF INTANGIBLES[1]

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Cloud computing presents a significant change in the way firms access digital technology and enables data-driven business models. Now, firms can acquire their storage, processing and software needs as a cloud computing service rather than making upfront fixed cost investments in capital. Yet, policies that encourage digital diffusion are still targeted towards investment in physical IT capital. This paper exploits 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 analytics. The adverse effects of the policy on cloud and big data adoption are particularly pronounced for small firms.

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I. INTRODUCTION

Increasingly, firms are relying on intangible assets such as data and less on tangible assets such as machines, equipment and factories (Corrado & Hulten, 2010; Haskel & Westlake, 2017). This new age of business models is based on voluminous, high-frequency data collection and analysis, referred to as big data (McKinsey, 2011; Niebel, Rasel, & Viete, 2019).[2] Data analytics are used to predict and automate a wide array of decisions – including customer service or identification of new markets (Economist, 2015). This shift towards data-driven business models is expected to increase the global total of stored data from 33 zettabytes in 2018 to 175 zettabytes by 2025, much of which will be stored in the cloud (Patrizio, 2018).

The arrival of the cloud has reduced the cost of data-driven business models, while the proliferation of smart-devices, sensors and Internet-of-Things has led to an explosion in the availability of data. Big data requires large amounts of flexible storage and processing power, which is often only feasible via the cloud. In the past, firms adopted data-analytics by making significant up-front large-scale investments in servers and software which were then maintained by teams of IT specialists. Today, firms increasingly acquire their data storage, processing and software needs as a cloud computing service from third party providers offering "pay as you go" subscriptions, with near limitless scale-up capability.[3] Looking forward, the diffusion of cloud will further facilitate emerging technologies including artificial intelligence and other predictive tools that rely on big data (Columbus, 2018).

Recent empirical research has found that the adoption of cloud and digital services more generally, leads to a number of important performance gains by firms, such as through the growth and higher survival rates of young firms and the reorganization and geographic dispersion of incumbents (DeStefano, Kneller and Timmis 2020; Jin and McElheran 2017). Since cloud appears to be important for firm performance and the ability to adopt new big data business models, it is important to understand the extent to which current policy environments influence the adoption of these tools.

Despite the likely performance gains from cloud adoption along with the use of other intangible assets, policies designed to encourage digital diffusion are still overwhelmingly

[2] Goldfarb at al. (2019) provide early evidence that machine learning and big data could be viewed as a general purpose technology.

[3] The growth of this new way of accessing IT has been rapid (Van Ark, 2016; OECD, 2015). Cloud services were first launched by Amazon Web Services in 2006 and cloud expenditures have grown at a rate 4.5 times faster than those on traditional IT investment since 2009 (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).

directed towards investment in tangible forms of IT capital. Every country within the OECD has some form of capital incentive policy, including tax allowances, subsidies, grants and other instruments targeted towards IT hardware, software and/or tangible capital investments more generally (Tax Foundation, 2018). Such tax schemes stimulate IT investment by decreasing the user cost of capital (Jorgenson, 1963; Hall and Jorgenson, 1967) and often explicitly target small and medium sized firms (SMEs) in order to help alleviate the financial constraints faced by these firms making adoption decisions.

This paper provides, to our knowledge, the first empirical assessment on the impact of capital incentive policies on cloud computing and big data adoption. In particular, the analysis will examine whether a recent capital incentive program affected the diffusion of cloud technologies and big-data analytics amongst UK firms. This paper relies on novel firm-level data which captures the adoption of cloud computing services and big data along with information on investments in tangible capital, including total IT investment and hardware investment. This data is combined with information on the rollout and adjustments to a capital incentive policy in the UK and used as a quasi-natural experiment. Since the intervention of the policy, the qualification thresholds have changed several times, allowing us to assess both cross-firm and time effects on the decision to adopt cloud and big data.

Policies explicitly incentivizing capital investment may discourage the adoption of cloud. Since cloud services offer very similar data, storage, computing and application functions that are offered by more traditional investments in hardware and software there is reason to believe that they are likely (partial) substitutes. Such outcomes however are not guaranteed though, especially when the focus is widened to related technologies such as big data. There are reasons to expect technologies that are data intensive such as big data, may be stronger complements to cloud than traditional IT (McKinsey, 2011, 2017; Goldfarb et al 2019). For example, the distinct feature of cloud is that it allows firms to alter their data storage and processing needs rapidly with near infinite scalability, lowering adjustment costs. Data intensive processes may therefore decline alongside the use of cloud technologies because of capital incentive programs.

The response to the capital incentive policy is likely to differ across firms. As already mentioned, empirical assessment of capital incentive programs find that young and small firms, who are often credit constrained, typically respond very strongly (Cummins et al., 1994; Hassett and Hubbard, 2002; Gorodnichenko and Schnitzer, 2013). These are the same firms that appear to be adopting cloud at a faster rate relative to previous IT technologies. The large up-front fixed costs necessary for physical digital technology purchases favors large firms with scale over which to spread these costs (Calvino, DeStefano and Timmis, 2017; Calvino, Criscuolo and Menon, 2016; Brynjolfsson et al., 2008).[4] In contrast, purchasing IT services through the cloud shifts IT expenditures to a largely variable cost. This is thought to favor cloud adoption by smaller, younger, credit-constrained firms who can adjust their IT needs quickly in response to the demand shocks they face. A nascent academic literature has also begun to show that cloud technologies are used by, and disproportionately benefit, small and young firms. Bloom and Pierri (2018) found for example, that the adoption of cloud is occurring at a faster rate amongst young and small businesses in the US than for previous IT technologies. Jin and McElheran (2017) report evidence that purchases of IT services are related to significantly higher survival and growth among young establishments, while DeStefano, Kneller and Timmis (2020) find evidence that cloud adoption leads to faster employment and sales growth for young firms.[5]

The empirical analysis of this paper centers on the UK Annual Investment Allowance (AIA).[6] The AIA was introduced in the financial year 2008-2009 and allowed firms to deduct the cost of investment in capital against profits up to a certain threshold (up to £50,000). The stated aim of the policy was to increase capital investment. These thresholds were raised significantly in 2011 (investments up to £100,000) and 2014 (investments up to £250,000). There is evidence that this represented a large change in the user cost of capital for affected firms. For example, for the 2011 reform Liu and Harper (2013) estimate that the user cost of capital decreased for these firms by 28-31%, depending on the method of finance.[7] This policy change that is particularly salient to questions of cloud and big data adoption, as the timing of the AIA coincides with the arrival of cloud services in the UK. 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 using a difference-in-differences approach. The AIA impacted the marginal investment cost of some firms and not others, affecting the incentive to adopt cloud and big

[4] 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).

[5] They also find it leads to the reorganization of incumbent firms. This occurs through closing plants and moving employment further from the headquarters. Growth effects are also present for incumbents firms, but they are weaker than those for small firms.

[6] 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.

[7] 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).

data technologies of treated firms.[8] The variation in AIA over time allows us to examine within-firm changes in response to changes in the AIA threshold for treated versus control firms. 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 applied to examine the effects of employment protection legislation or R&D tax credits that also feature size thresholds (Bjuggren, 2018; Saez et al., 2019; and Bøler et al., 2015) and define firms' treatment status in our paper by the previous capital investment of a firm compared to future AIA tax-allowance thresholds. 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 their capital 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 (lagged second or third year values).

Overall, the empirical results suggests that AIA caused substitution away from the use of cloud by UK firms. We estimate that the AIA policy resulted in an 11% *reduction* in the propensity to adopt cloud by firms whose marginal cost of capital fell compared to the counterfactual. This compares to a mean rate of cloud adoption of 38% in our sample. These negative effects are stronger for cloud hardware services – related to the storage and processing of data – than compared to cloud software services. This suggests AIA may slow the diffusion of cloud-enabled data-driven business models.

We also find within our analysis that the AIA led to a *lower* likelihood of using big-data analytics for affected firms, with our estimates suggesting an effect of around 15%. There is also evidence of further differences according to firm size. Small and medium sized firms (SMEs) appear to responded particularly strongly to the AIA compared to large firms.[9] The estimates suggest that SMEs for whom the AIA makes capital investment less costly, are 37% less likely to adopt cloud technologies. We find that negative effects from the AIA for SMEs are present for both hardware and software cloud services, whereas for large firms the effects of the AIA are confined to cloud hardware services. Both SMEs and large firms reduced their use of big data analytics.

[8] 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.

[9] SMEs are defined in our analysis as firms with fewer than 250 employees. The majority of investment values by SMEs are below the thresholds used in the AIA policy. This limits our ability to explore alternative definitions of SMEs.

We subject these findings to a number of tests of their robustness including the way that we define treatment and control groups and dealing with any contamination from an earlier capital investment policy called the first-year allowance programme studied by Maffini et al. (2019). We also present in the paper estimates of local average treatment effects on cloud adoption.

While not the focus of the paper, the analysis 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] In this paper we are able to show that firms experiencing a fall in their marginal cost of investment because of the AIA increased their investment in total tangible capital, total IT and hardware, as one would expect. This reinforces the interpretation of negative effects on cloud adoption due to substitution effects. We also find that standard tests for pre-treatment trends for investment in physical capital are satisfied and that and there are no effects when using placebo tests for false investment thresholds.

Given the data available, 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, 2020). 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).[11] 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

[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).

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

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).[12] A recent study by DeStefano, Kneller and Timmis (2020) find that the diffusion high-speed fiber broadband strongly predicts cloud adoption, particularly for those with fast expected fiber 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 and big data analytics, also connects the paper 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). Most of the recent slowdown is (tangible) investment simply reflects a shift towards expenditure on intangibles (Crouzet and Eberly, 2019). 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).

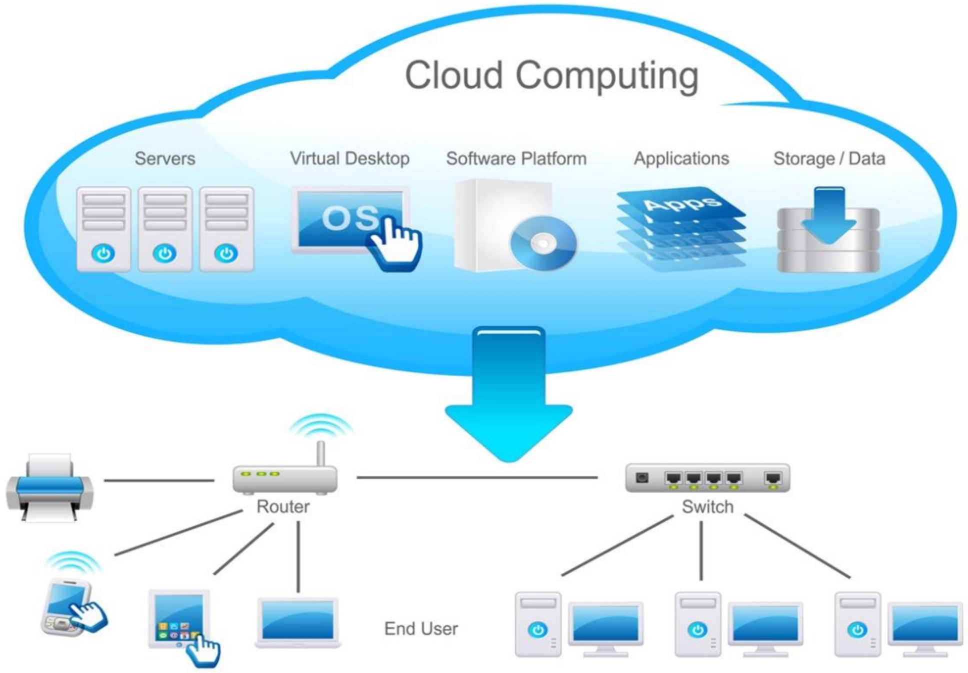
The paper continues as follows: Section II provides some discussion on the definition of cloud computing and the perceived benefits of the technology. Section III presents more details on the AIA policy, Section IV describes the data and Section V our estimation strategy. Section VI presents the main results of the paper for cloud, big data and differences across firms. Section VII presents robustness analyses and the results for capital investment and Section VIII concludes.

[12] Large firms are defined as those with more than 250 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 is considered 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 that 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 change 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 entering 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 organize. 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 decentralizing access to data, processing and software to many devices (DeStefano, Kneller and Timmis, 2020).

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 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). These large volumes of data require flexible storage and processing power that can be scaled up and down, which is often only available via the cloud (Iansiti and Lakhani 2020; 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 encouraging 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 includes IT capital. This policy was seen as a move away from a size, sector 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 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 positive effects 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 received considerable criticism (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 then occurred in May, and then within a

[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.
[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

special budget in June 2010 the AIA ceiling was to 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 was further increased 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 substantially during the sample period, specifically, the years ending in 2009, 2011, 2014 and 2015.[17] To put these numbers in perspective, in our data the 2008 median value of investment was £562,000. Investment of £50,000 is close to the 19th percentile of the distribution in 2008, £100,000 was around the 25th percentile of the distribution in 2011, and £250,000 was a little above the 35th percentile in 2014.

[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).

[17] We do not consider the fall in the AIA during the year ending 2013.

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. One potential policy was the First Year Allowance (FYA). The FYA was introduced before our sample period and withdrawn in 2008, making a reappearance in 2010 for one year.[18] This policy was similar to the AIA in that it provided tax allowances for investments in capital, but was targeted at small firms with revenue below £22.8 million.[19] To ensure that our 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 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.

There were also a number of changes to the standard corporate tax rate during the time period, which may affect the user cost of capital. The standard rate was cut from 30% to 28% for the fiscal year 2008-2009, to 26% in the fiscal year 2011-2012, 24% in 2012-2013, 23% in 2013-2014, 21% in 2014-2015 and to 20% in 2015-2016. The small company tax rate was reduced from 21% to 20% in the tax year 2011-2012. These are small changes compared to the AIA and as they did not differ across firms will be absorbed by common year effects.

[18] In this year businesses incurring expenditure in excess of the AIA cap that would have normally qualify for a 20% Writing Down Allowance were instead able to claim a 40% First Year Allowance instead.
[19] See Maffini et al (2019) for further discussions on the FYA.

IV.DATA AND SAMPLE STATISTICS

The research relies on four different types of data: cloud and big-data use by firms; details regarding the introduction and changes to the AIA; lagged firm investment to identify our set of treated firms and firm characteristics (used as controls) include, foreign ownership, age multi-establishment statute and so on. 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 yes/no questions on the firms use 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.[20] The first is a dummy variable equal to one if the firm uses any of the 7 different forms of cloud and zero if they use none of them. The second dummy variable, 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 (and zero otherwise). We anticipate that as the up-front costs of hardware are typically larger than for software, this group may be more sensitive to capital investment policy. The third group, which we label software, is a dummy variable equal to one if the firm uses any of the cloud email, office software, CRM software and finance and accounting software (and zero otherwise).[21] 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 the rollout of high-speed fiber in the UK and consistent with the assumption of DeStefano Kneller and Timmis (2020), we assume zero cloud adoption for all firms (giving a maximum of three observations per firm).

The measure of big data is constructed from a yes/no question asked in the 2015 version of the E-commerce survey. From this we construct a variable called big data, which is a binary variable equal to 1 if an enterprise is analysing big data via either of the following methods:

[20] We list these questions in the Appendix.

[21] 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.

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.[22] The ONS define big data in the E-commerce survey by characteristics including: (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 the analysis of big data as the use of techniques, technologies and software tools for analysing big data from the business's own or other data sources. The dataset also provides further information on whether these big data analytics are conducted in-house, through an external contractor, or both. Again, we assume that the collection and analysis of big data is equal to zero for all firms in 2008 (and therefore there is a maximum of two observations per firm).

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). IT investment data is available for a shorter time period, beginning in 2008 and ending in 2014. Finally, data on firm control variables (age, multi-establishment status, foreign ownership) are sourced from the UK business registry – the Business Structure Database.

Table 2 below provides summary statistics of the main variables. We find 38% of firms in our sample use at least one form of cloud computing services in 2013 or 2015.[23] 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. The mean value of total investment (log thousands of real UK pounds) within the

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

[23] We provide summary statistics for 2013 and 2015 for these variables as this corresponds to the years these questions were included in the E-Commerce Survey. We provide separate summary statistics for 2015, the year we observe the use of big data by the firm in Appendix Table A1.

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 establishments, 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 (5 years old or younger).

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
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-establishment	0.679	0.467	56,676
Number of establishments	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 of capital incentive programs on cloud and big-data adoption we use changes in the AIA to identify a set of treated firms for whom the marginal incentives to invest in capital have fallen. Treating this as a natural experiment we use a difference-in-differences regression expressed as follows:

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

Where the variable y_{it} represents the outcome for cloud/big-data adoption of firm i in period t.[24] AIA_{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-establishment and foreign ownership, α is a constant term and ε_{it} is an error term. Given that the AIA's effect on the marginal cost of investment is itself a function of investment, a DID design is preferable to say a regression discontinuity design. Such a design would capture the effect of treatment only in the vicinity of the threshold, thereby ignoring smaller firms for whom both capital incentive programs and the cost advantages of cloud have been thought to have the greatest relevance.[25]

In this framework, firms could of course adjust their capital investment to a point just below the AIA threshold posing a selection problem. In the periods preceding the introduction of the AIA, we show that there is no evidence for such effects. Figure 2 plots the distribution of total capital investment for 2006-2008, where we hone in on the potentially affected firms by focusing on firms whose investment was between £1 and £100,000 per year.[26] There is no visible discrepancy around the £50,000 threshold in the firm-year observations before the introduction of the AIA in 2009. We repeat this exercise for the increase in the threshold to £100,000 in 2011 (we show the values for investment in 2008-2010) in Figure 3 and for the

[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.

[25] Unfortunately, we are not able to directly consider whether AIA-induced changes in cloud adoption subsequently affect the diffusion of big-data analytics, because it would likely fail the exclusion restriction. Big data adoption could be also achieved by investment in tangible IT hardware (such as servers), which would be influenced by the AIA capital incentive policy.

[26] To avoid the suppression of cells with small numbers of observations by the data providers we use three years of data within these figures.

increase in the threshold to £250,000 in 2014 (we show the values for investment in 2011-2013) in Figure 4. Again we find no visible discrepancies in total investment around these future AIA thresholds.

Figure 2: Distribution of investment around the AIA threshold of £50,000 in 2006-2008

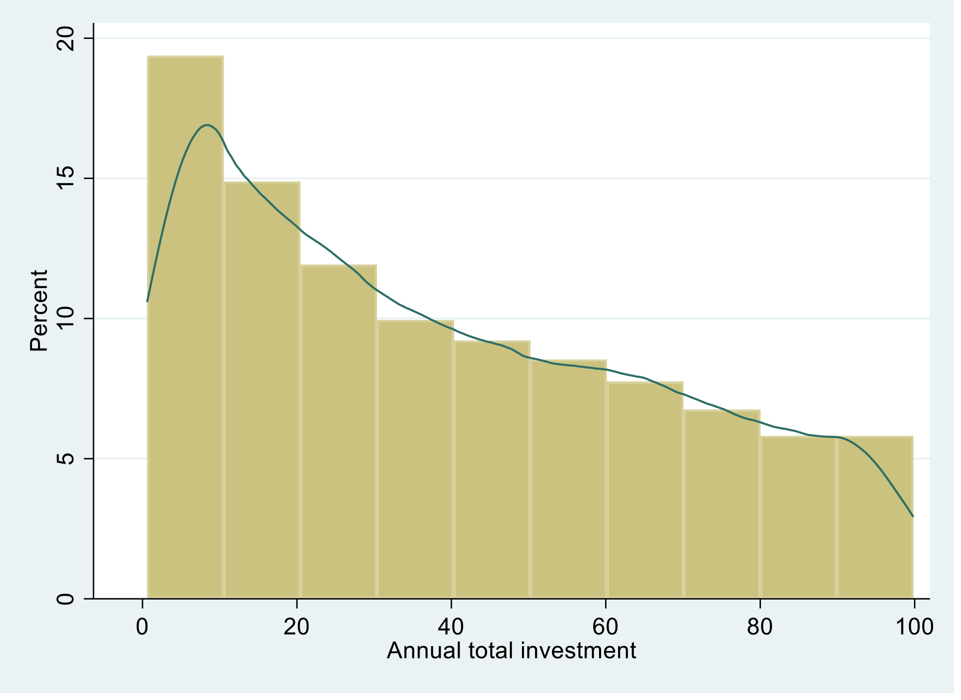


Figure 3: Distribution of investment around the AIA threshold of £100,000 in 2008-2010

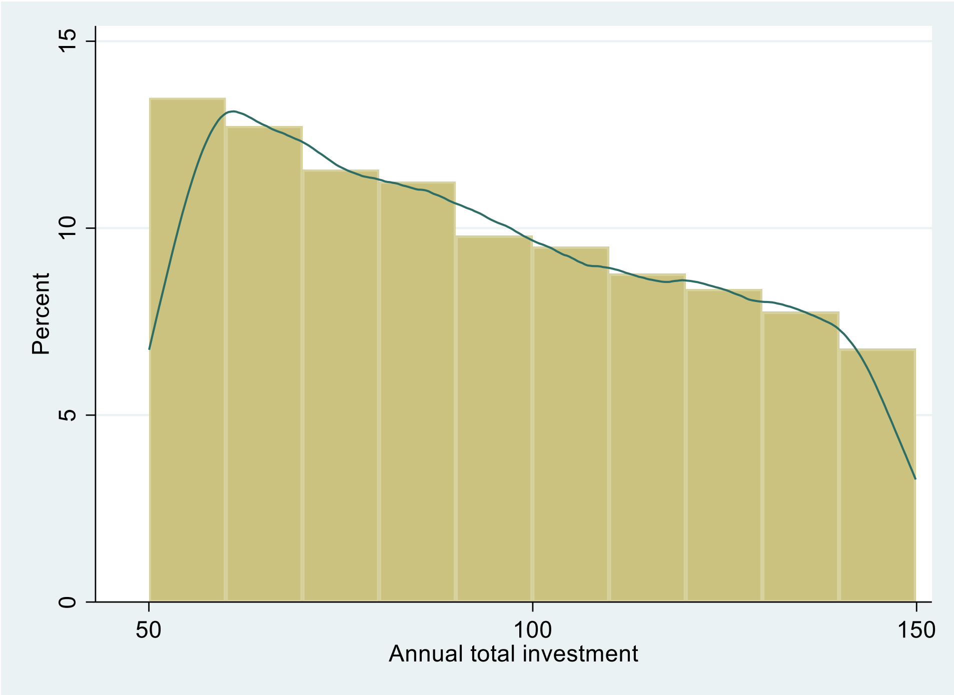
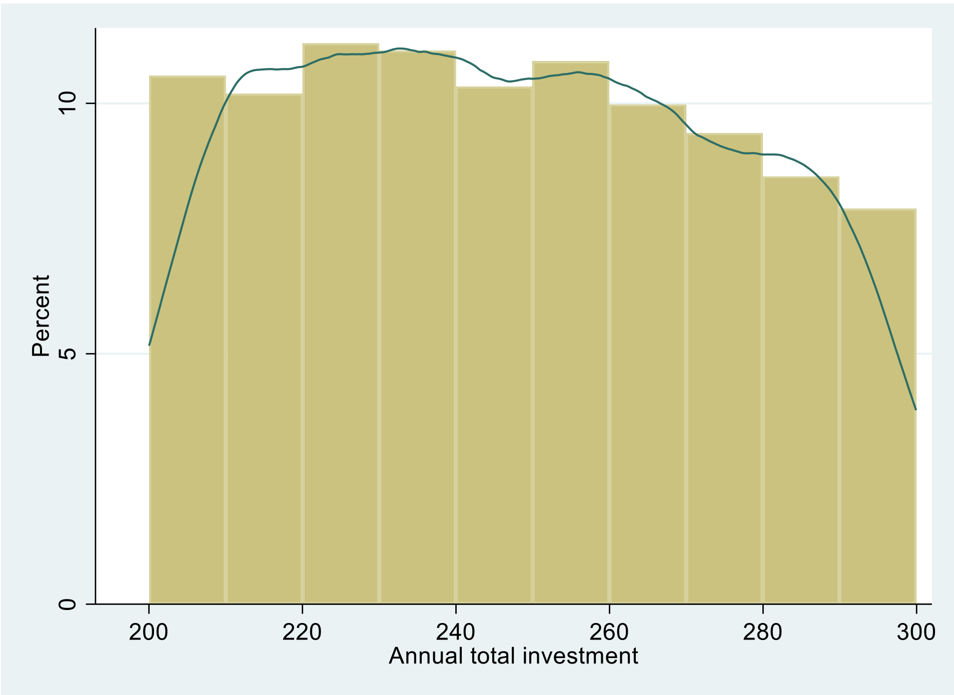


Figure 4: Distribution of investment around the AIA threshold of £250,000 in 2011-2013



Despite the evidence presented in Figure 2 to Figure 4 suggesting that firms did not select into treatment or control prior to the policy introduction/changes that we study, we follow the empirical approach used in Bøler et al. (2015), Bjuggren (2018) and Saez et al. (2019), and allocate firms into treatment and control groups based on their capital investment in time periods prior to the reform literature. AIA_{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. Given this specification, 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 (Chrinko, 1993; Maffini et al., 2019) we identify treated firms by comparing the average value of their total investment in the previous two years to the AIA threshold.[27] To address concerns of anticipation, we examine robustness to the use of averages measured across the previous three-years, as well as using only a single lagged two or year three year investment value. We explore the issue of anticipation effects further in Section VI of the paper.

The treated firms, those for whom the marginal incentive to invest has been altered, differs across years. For the introduction of the AIA, treated firms are those whose (prior average) capital investment would place them below the threshold of £50,000 (this represents the 19th percentile for total investment in that year). For these firms, their marginal cost of IT capital investment falls as a result of the AIA allowance implementation. 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 case firms with investment above the threshold. For the 2011 reform, where the threshold was moved from £50,000 to £100,000 (this represents the 25th percentile for total investment in that year), treated firms are those firms whose (prior average) investment lies between £50,000 and £100,000.[28] 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 in that year) that we consider to be treated by the change to the AIA.

[27] By way of illustration, the correlation between the average value of investment in 2006 and 2007 and investment in 2008 is 95.3%. Similarly high correlations are found for other years.

[28] 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 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. The standard 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. It follows that the adoption by treatment and control firms is zero before this year and that the treatment and control group share common pre-treatment trends by construction. Instead, 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 use 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

Cloud Diffusion

The AIA was designed and implemented by policy makers with the objective to increase the stock of digital technologies through investments in traditional physical IT capital. However, these policies may unintentionally discourage the adoption of digital services, such as cloud. This is what we find in our data. While the AIA succeeded in encouraging firms to invest in physical capital investment including in IT capital, it also led to a *reduction* in the likelihood for treated firms to adopt cloud technologies. [29] In regression 1 in Table 3, 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 11%. The magnitude of the estimated coefficient is relatively large compared to the mean rate of cloud adoption, which is 38% in our sample. 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.[30]

The detailed nature of the UK data allows us to further explore how the AIA policy is linked to the propensity to adopt different types of cloud services. Within Table 3 we begin by separating the aggregate measure of cloud (regression 1) into cloud hardware (regression 2), and its subcomponents: file storage (regression 3), businesses databases (regression 4), and data processing (regression 5). We find the AIA capital incentive strongly predicts a reduction in the rate of 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. When separating out types of cloud hardware, significant effects are found for 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 less precisely identified compared to the other outcomes.

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[29] 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.

[30] We have tested the robustness of this finding to the use of a logit estimator. As the year 2008 perfectly predicts non-adoption of cloud in the data, and the data measures cloud use in 2013 and 2015 – which are both periods after the 2009 and 2011 reforms of the AIA we conduct this for the 2014 AIA reform only (and therefore using 2013 as the pre-reform period and 2015 as the post-reform period. In this regression the AIA reform has a negative and statistically significant effect on cloud adoption (coeff:-0.356 s.e. 0.180). Similar results are found for a probit estimator.

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 3 reporting the effects of the AIA policy on the use of any type of cloud 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).[31] We also note that the coefficient estimates and standard errors for the separate types of cloud services in regressions 7 to 10 are both small, indicating that these zero effects are estimated with a reasonable degree of precision.

[31] 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 3: 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-establishment 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 involved require large amounts of storage and processing power.[32] Cloud offers storage and processing capabilities in ways that are more flexible and cost effective than installing the physical server infrastructure (McKinsey, 2011).[33] This opens the possibility that capital investment policies in the UK may also act to slow the diffusion of big data analytics across firms. Alternatively, the AIA also acts to reduce the relative cost of capital versus labor. To the extent that this makes the firm more IT capital intensive it may encourage the adoption of big data and the technologies that allow for its analysis.

We find evidence supporting the view that AIA discouraged the use of big data by UK firms. According to our estimates, the AIA thresholds reduced the use of big data analytics by around 15% (regression 1 in Table 4). In the remaining regressions in Table 4 we disentangle big data adoption further by considering whether the analytics are conducted internally within the firm, through external data analytics providers, or both. On the one hand, since cloud computing is purchased from 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 analyse big data only externally or only internally – with estimated coefficients very close to zero (see regressions 2 and 3 in Table 4). 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 through a combination of both internal and external providers.

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

[33] 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 4: 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-establishment 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. Measures of big-data analytics 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 performance strongly suggests a difference according to the size of the firm. 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 new 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 small 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 young and small firms and is found to increase their scale and productivity (DeStefano Kneller and Timmis, 2020). This echoes a finding within the capital incentives literature, which suggests that such policies act particularly strongly on firms that are credit constrained, who are typically also likely to be smaller. Cummins et al. (1994), 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 SMEs and large firms, where we categorise SMEs as those with employment below 250 employees in 2008.[34] We report the results from this exercise in Table 5, for the aggregate measure of cloud (regression 1), cloud hardware and software separately (regressions 2 and 3) and the two

[34] Defined in this way there are 2,058 firm-year observations on SMEs and 10,584 firm-year observations on large firms. We have tried other similar thresholds with quantitatively similar results. We have also tried using total employment of the firm. In all cases we find that the response of large firms is reduced compared to that of smaller firms.

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 SMEs compared to large firms. The AIA policy caused both SMEs 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 databases. For SME firms we find that there are also effects for other types of hardware (See for example in Table A4 where 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 program also affected the adoption of various forms of cloud software for SMEs (and in Table A4 this holds irrespective of the various forms of cloud software).

The estimated effect on SMEs firms are particularly strong. In regression 1 in Table 5, the estimates suggest that SMEs for whom the AIA makes capital investment less costly, are 38% less likely to adopt cloud technologies. They are 26% less likely to adopt hardware forms of cloud and 36% less likely to adopt software. The latter result is of interest as it indicates complementarity between different forms of cloud for SMEs, 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 SMEs and large firms are affected by the AIA policy, and that the effect is stronger for the smaller-medium sized firms compared to large firms. For the use of both internal and external big data (see regression 5) the results are modified somewhat. For this type of big data analytics we find that both SMEs and large firms treated by the AIA capital incentive are less likely to use this form of big data analytics, and that we cannot reject the hypothesis that the estimated effects is statistically similar in size for both of these groups of firms (given by the lack of statistically significance for the AIA SME dummy interaction).

Table 5: 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
* SME dummy	(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-establishment 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. SME dummy is a zero-one indicator for whether the firm had less (yes=1) than 250 employees in 2008 (=0 otherwise). 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 thus 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 6 we consider separately the changes in the AIA threshold in 2009, 2011 and 2014. Given the results in the previous section we allow this effect to differ for SMEs and large firms.

Within Table 6 we continue to find that the AIA tax policy led to a reduced likelihood that the firm adopts cloud computing by SMEs, where this effect is statistically significant for all of the reform years (see regression 1). This would tend to suggest that the effect of the AIA capital incentive may permanently delay the adoption of substitute technologies such as cloud for these types of firms.[35] 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 may suggest that the effect of the capital incentive policy for large firms is to delay adoption, but not permanently so. For software we

[35] 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.

find no significant effects from any reform year for large firms, whereas the results for cloud hardware tend to mirror those for the aggregate variable.

For the adoption of big data technologies we find strong effects for most of the waves of the AIA and fewer differences across SMEs and large firms (either the general measure of whether it is done using a combination of internal and externally albeit across different years). This would appear to indicate that while the AIA policy delayed rather than permanently prevented the adoption of cloud technologies, the lack of experience of using cloud technologies may have had more permanent impacts of complementary technologies such as big data analytics. For the 2011 and 2014 AIA reforms we find that these effects for big data were stronger for SMEs compared to large firms.

Table 6: Separate AIA Events

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* SMEs	-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* SMEs	-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* SMEs	-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-establishment 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. SME dummy is a zero-one indicator for whether the firm had less (yes=1) than 250 employees in 2008 (=0 otherwise) 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 series of robustness tests of the earlier baseline results. We begin by considering the robustness to alternative ways of determining treated firms. Next we consider an alternative tax incentive in the UK, the First Year Allowance, which may be confounding the prior estimates. Finally, we assess the robustness of the attention to treat framework. To do so, we employ 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.

Alternative Treatment Groups and Alternative Tax Incentives

In regressions 1, 2 and 3 of Table 7 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 Table 7. We begin by using the average of firms' investment over the previous three years to determine their treatment status (regression 1).[36] In regressions 2 and 3 we use the value of their lagged investment in either period t-2 or 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 into the estimates.

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.

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

[36] 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.

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, in regression 4 in Table 7 we exclude firms in our sample that ever had 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 results are robust to the exclusion of these firms (see regression 4). The signs and statistical significance of the use of cloud services are consistent with the baseline results in Tables 3 and 4.[37]

Table 7: Alternative Treatment Groups

Regression No.	*(1)*	*(2)*	*(3)*	*(4)*
Variables	*Cloud*	*Cloud*	*Cloud*	*Cloud*
Treatment group	*Averages based on 3 year lags*	*2 year lag*	*3 year lag*	*Accounting for first year allowances*
AIA treatment	-0.070**	-0.115***	-0.065**	-0.124***
	(0.033)	(0.028)	(0.029)	(0.034)
Observations	12,444	12,642	12,444	11,006

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-establishment dummy, foreign owned dummy and log age, not reported for brevity. Regressions 1 uses the average of previous 3 years firm investment to determine the treatment group. Regressions 2 and 3 use investment in time t-2 and 2-3 to determine the treatment group. Regression 4 excludes firms in the sample that ever had sales of less than £22.8 million in any year during our sample period. 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.*

[37] 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 A5). Again, the results are consistent with the baseline results in Tables 3 suggesting our results are not being driven by the presence of outlier firms in our sample.

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 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 employ 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 8 we report the 2SLS estimates of cloud adoption on AIA, all cloud along with hardware and software cloud services, respectively. In the first stage, we find that reduced investment costs using lagged investment is a strong predictor for the reduction of contemporaneous investment costs, 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.[38]

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

[38] We continue to find no effect on the adoption of the disaggregated types of cloud. We include these results in Appendix Table A6 for completeness.

whose investment increases above AIA threshold between t-2 and t are generally growing rapidly and so may be more likely to invest in cloud anyway – without the investment incentive.

Table 8: 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-establishment 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.*

Capital Investment, pre-treatment and placebo tests

In this section we focus on the effects of the AIA on capital investment. We include tests of pre-treatment trends, difference-in-difference estimates of the intention to treat effects of AIA and the results from placebo regressions.

As already discussed, as we study the period of adoption for a new technology in cloud and big data analytics the assumption of pre-treatment trends in the outcome variables of interest are imposed. No firms can adopt before the technology began to diffuse. We instead examine pre-treatment trends in total investment, reporting the results for IT investment and IT hardware investment in Figures A1 and A2 in Appendix A. The investment data are available on an annual basis for the period 2008 to 2014. Owing to the fact that this leaves only one year of pre-treatment data for the 2009 introduction of the AIA, we focus our attention on the 2011 and 2014 reforms, although we report the results for the 2009 in Appendix Figures A1 to A7 for completeness.

To construct each figure 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, where time - we present year on changes from t-3 to t+3. For the 2014 reform we present results for t-3 to t, as the investment data end in 2014. The regressions corresponding to each graph are reported underneath each graph. We also report in the figure 90% confidence intervals.[39]

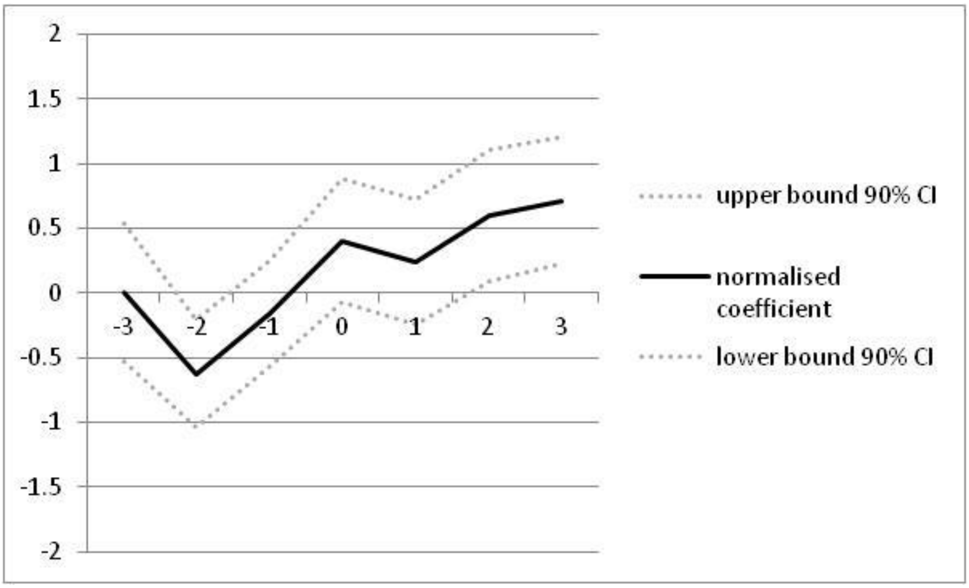
The objectives of these figures are twofold. Firstly, they illustrate how long it takes for changes in the capital allowance to materialise into changes in the investment decisions of treated firms. Maffini et al (2019) show that earlier tax incentives often take several years to translate into changes in investment decisions. Secondly, by also examining changes to the allowance in 2011 and 2014, 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.[40]

Two aspects of the results are of interest. Firstly, the results in Figures 5 and 6 indicate that there is no significant difference in investment between treated and control firms in the year prior to the introduction of the AIA policy. 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. Secondly, in the post-treatment time period the effect of the policy on treated firms takes some time to materialise. As shown in the Appendix the effect of treatment differs very little according to the type of capital over time.

[39] These results are similar if we separate SMEs and large firms. Mafini et al. (2019) report that smaller firms, who pay corporate taxes in arrears in the UK, responded immediately to a change in first year allowances in the UK. They interpret this as evidence that it is changes in user costs and not cash flow effects that drive their results. Our results suggest a delayed investment response by SMEs, suggesting cash flow changes may be important during the period that we study.

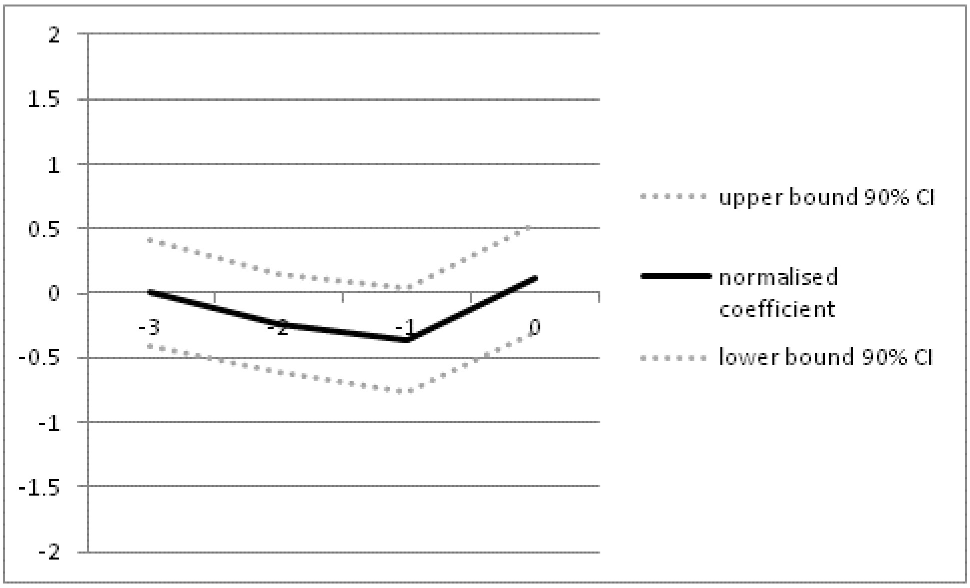
[40] The data sample for the UK begins in 2008 and it is therefore not possible to examine potential anticipation effects of the policy more than one year before the AIA was introduced.

Figure 5: Total Investment, 2011 AIA change



Notes: The figure illustrates the relationship between the change in the AIA in 2011 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: Total Investment, 2014 AIA change



Notes: The figure illustrates the relationship between the change in the AIA in 2014 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.

In Table 9 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. [41]

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 9 we find that the AIA incentivises firms to invest in capital by decreasing the user cost of capital and/or by relaxing financial constraints.[42] 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.[43] Given the estimated change in the user cost of capital reported by Harper and Liu (2013) of between 28% and 31%, depending on the method of finance, these effects appear large. We note that the effect of investment policy changes have found to be greater when firms are credit constrained and when the change in policy is anticipated to be only temporary. 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 or at least not particularly capital intensive. Secondly, these effects are averages 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 9: AIA Capital Allowances and Investment

Regression No.	*(1)*	*(2)*	*(3)*
Variables	*Total Investment*	*IT Acquisitions*	*Hardware Acquisitions*
AIA treatment	0.737***	0.415***	0.380***
	(0.084)	(0.056)	(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-establishment 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.*

[41] We use Table A7 in the Appendix to describe the effects on investment of the various AIA waves.

[42] The absence of firm balance sheet data prevents analysis of the user cost of capital. Thus, 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.

[43] 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 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. As previously noted, as we study the adoption of a new technology common pre-trends holds for cloud adoption and big data prior to its invention. To provide support for this assumption we instead use an indirect test, examining the effects of a placebo change in the AIA threshold. Our key identifying assumption is that firms have a common trend, in the absence of changes in the AIA policy. While this is not directly testable, one indirect test is to examine a placebo change in the AIA threshold. We consider three such versions, associated with the 2009 introduction of the AIA and then the 2011 and 2014 reforms. For the 2009 placebo test we consider a placebo increase in the AIA threshold from £50,000 to £100,000 in 2009 (rather than zero to £50,000 in reality); for the 2011 test we consider an increase in the AIA threshold from £100,000 to £150,000 in 2011 (rather than £50,000 to £100,000 in reality); and for the 2014 placebo test we consider an increase in the AIA threshold from £250,000 to £300,000 in 2011 (rather than £100,000 to £250,000 in reality). These are reported as regressions 1 to 3 in Table 10. For these placebo firms, their AIA threshold did not change in reality, with no change in their marginal cost of investment and therefore we should observe no investment response. We compare these placebo firms against the remaining control firms (i.e. we exclude firms that were genuinely treated by the 2009, 2011 or 2014 AIA changes).[44] The placebo treatment is then estimated equivalently to the reduced form baseline estimates in Tables 3 and 4. Finally, we note that as the measures of cloud are observed only several years after the AIA treatment it makes sense to estimate these only for total investment (the placebo treatment and control groups would become muddled for cloud).

We find the placebo change in the AIA allowance is associated with no significant change in total investment (see Table 10). The estimated coefficients are smaller compared to the real treatment estimated effects and the standard errors are of a similar size. This would tend to rule out the presence of confounding factors that explain the previous findings and suggest those firms just above the true thresholds have similar trends to other firms in the control group.

[44] To do this we place restrictions on the data in terms of both the cross-section and time series. For the 2009 placebo reform we restrict the data to before 2011. For the 2011 reform we restrict the data to before 2014. In the 2011 placebo reform we exclude firms that have and investment 2 years prior to the reform below £50,000 (i.e. were treated by the 2009 reform) and for the 2014 placebo reform we exclude firms that have and investment 2 years prior to the reform below £100,000 (i.e. were treated by the 2011 reform).

Table 10: Placebo tests of Artificial AIA Changes on IT investment decisions

Regression No.	*(1)*	*(2)*	*(3)*
Variables	*Total Investment*	*Total Investment*	*Total Investment*
Treatment group	*2009* *£50k-£100k*	*2011* *£100k-£150k*	*2014* *£250k-£300k*
AIA treatment	0.237	0.156	0.039
	(0.174)	(0.117)	(0.178)
Observations	9,728	21,360	19,701

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-establishment dummy, foreign owned dummy and log age, not reported for brevity. 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.*

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 forms of IT ownership 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 fiber broadband (see DeStefano, Kneller and Timmis, 2020), 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 effect on the cloud producing sector matters by 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. If, as Goldfarb et al. (2019) suggest, and machine learning/big data are a general purpose technology this may have important effects on longer term growth. General purpose technologies are characterized by virtuous circles of innovation between those sectors creating and those using the technology (Bresnahan and Trajtenberg, 1995). 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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Data References

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APPENDIX

Types of cloud in the E-commerce survey

Does this business buy any of the following cloud computing services used over the internet?

- *Databases: Hosting the business' database(s) , as a cloud computing service*
- *Storage of files: Storage of files , as a cloud computing service*
- *Processing Own Software: Computing capacity to the business' own software, as a cloud computing service*
- *Software: Office software for example word-processing or spreadsheets, 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*
- *Email: Email, 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	Not 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
Multi-establishment	0.316	0.624	0.585	0.569	0.729
Number of establishments	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-establishment 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-establishment 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***
* SME dummy	(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-establishment 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. SME dummy is a zero-one indicator for whether the firm had less (yes=1) than 250 employees in 2008 (=0 otherwise). Robust standard errors clustered at the firm-level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.*

Table A5: Capital Allowances and Investment in IT Capital vs Cloud Adoption, excluding larger investors

Regression No.	(1)
Variables	Cloud
AIA treatment	-0.105***
	(0.033)
Observations	11480

*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-establishment dummy, foreign owned dummy and log age, not reported for brevity. Regressions 1 uses the average of 2 year lagged firm investment. Excludes firms with investment exceeding £10million. 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: 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

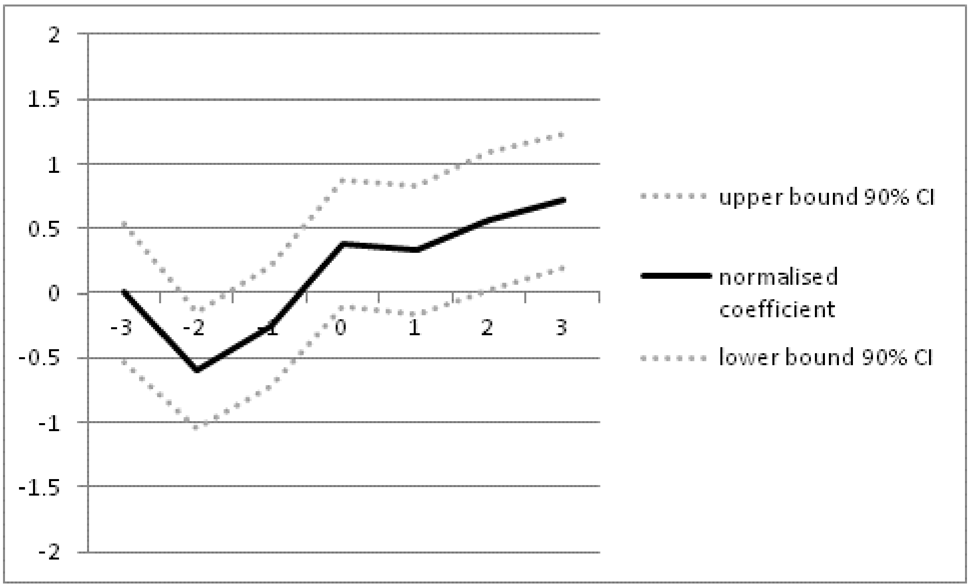
*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-establishment dummy, foreign owned dummy and log age, not reported for brevity. "AIA treatment – lagged investment" is constructed using firms' 2 year average lagged investment (consistent 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 A7: 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 2009	1.690***	0.845***	0.765***	-0.058
	(0.152)	(0.089)	(0.080)	(0.039)
AIA treatment 2011	0.194	0.252**	0.251***	-0.235***
	(0.131)	(0.101)	(0.091)	(0.085)
AIA treatment 2014	-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

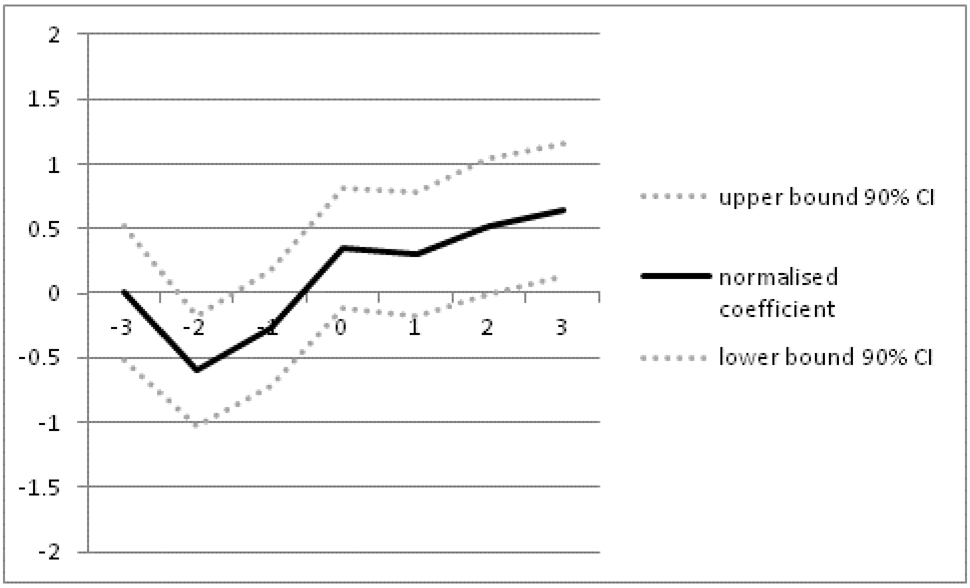
*Notes: All regressions include year and firm fixed effects, as well as firm controls of lagged investment, a multi-establishment dummy, foreign owned dummy and log age, not reported for brevity. Regressions use average of previous 2 years firm investment to determine the treatment group. The estimated 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.*

Figure A1: IT Investment, 2011 AIA change



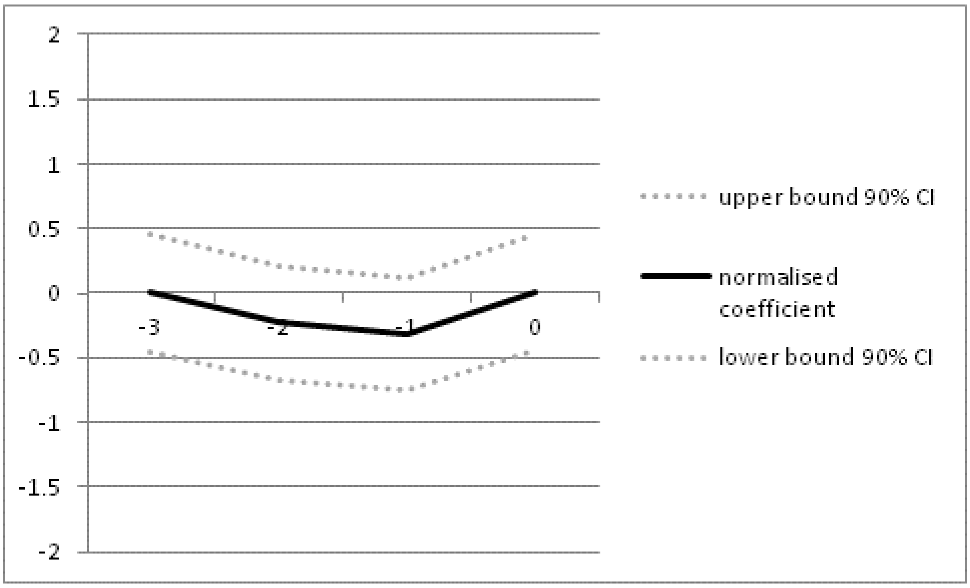
Notes: The figure illustrates the relationship between the change in the AIA in 2011 on IT acquisition for the treated firms. The figure is calculated by regressing the IT acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure A2: IT Hardware Investment, 2011 AIA change



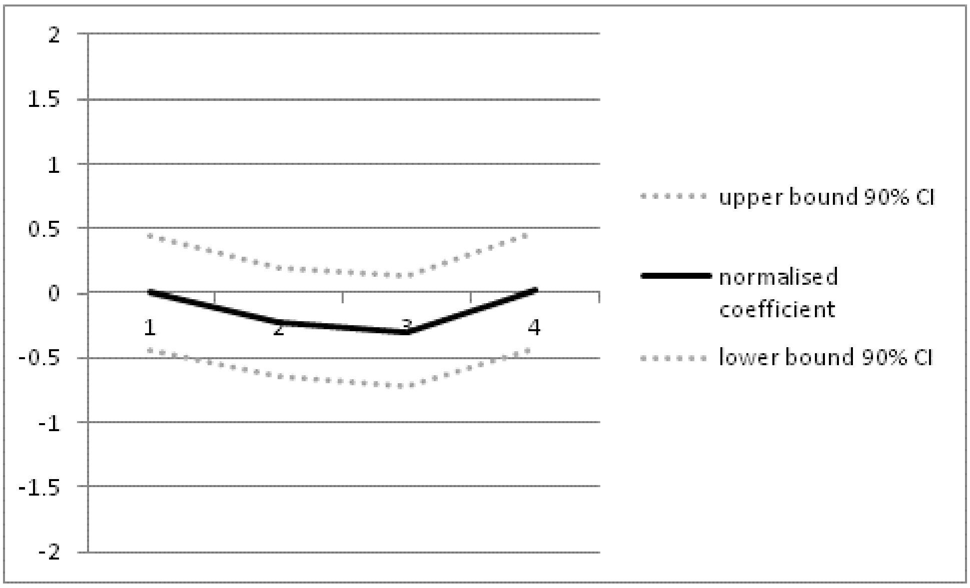
Notes: The figure illustrates the relationship between the change in the AIA in 2011 on hardware acquisition for the treated firms. The figure is calculated by regressing the hardware acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment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

Figure A3: IT Investment, 2014 AIA change



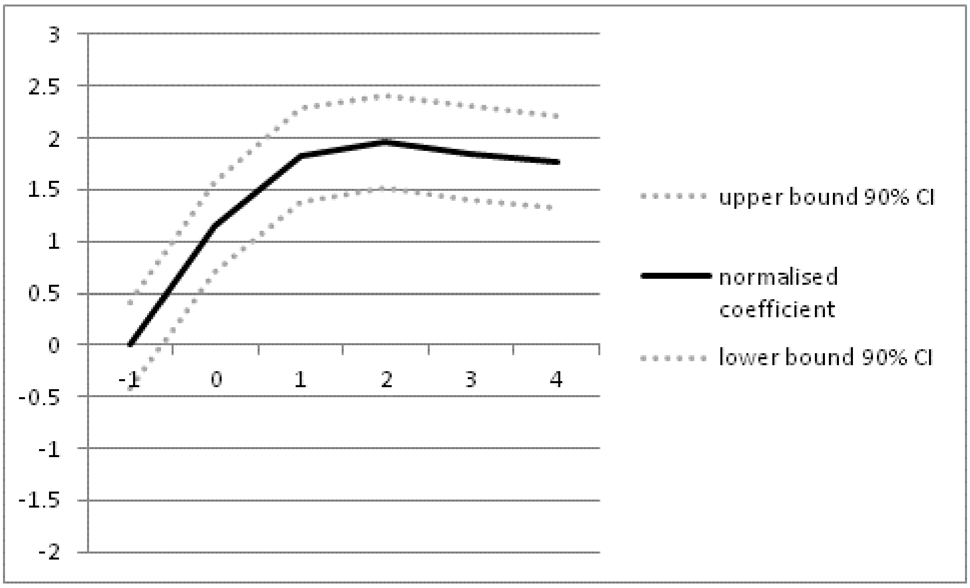
Notes: The figure illustrates the relationship between the change in the AIA in 2014 on IT acquisition for the treated firms. The figure is calculated by regressing the IT acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure A4: IT Hardware Investment, 2014 AIA change



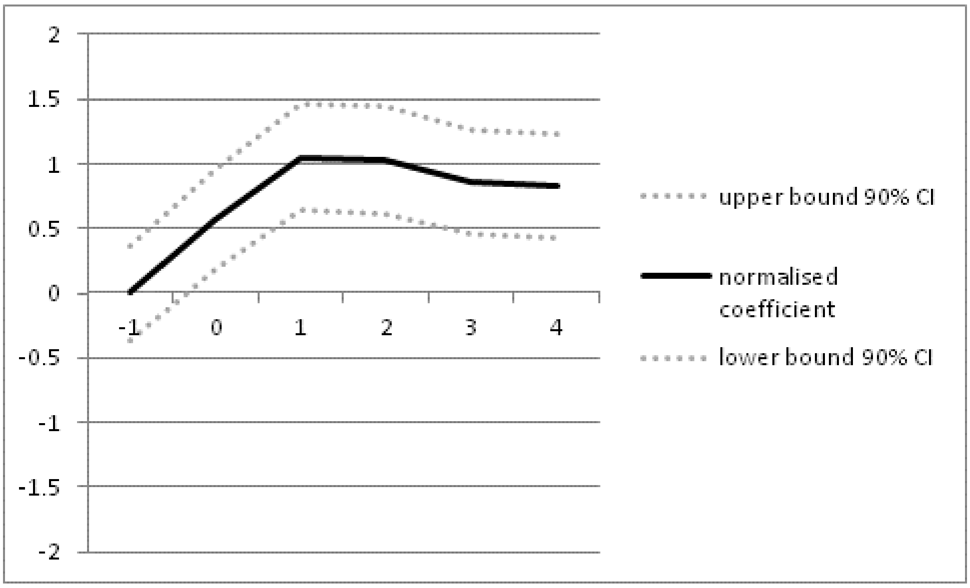
Notes: The figure illustrates the relationship between the change in the AIA in 2014 on hardware acquisition for the treated firms. The figure is calculated by regressing the hardware acquisition on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure A5: Total Investment, 2009 AIA change



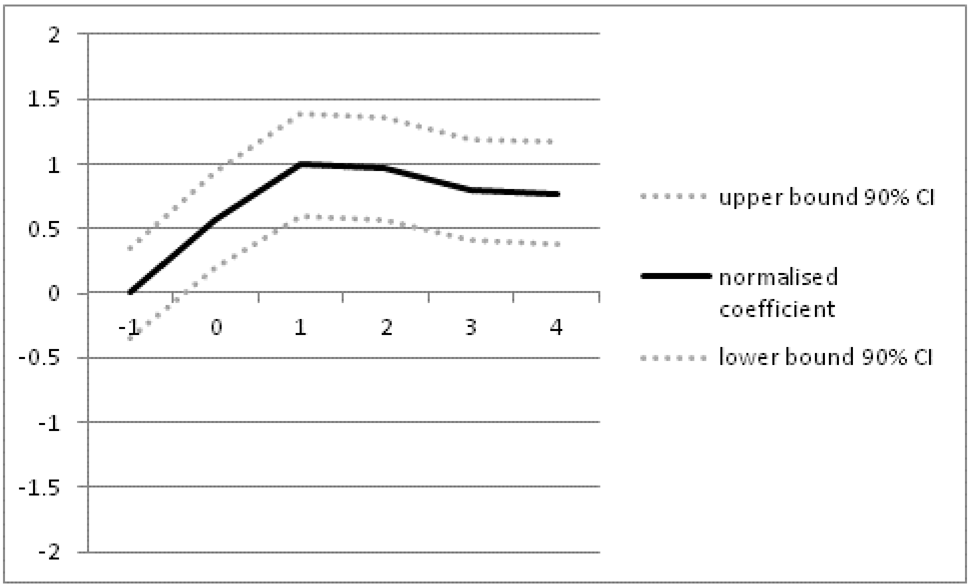
Notes: The figure illustrates the relationship between the introduction of the AIA in 2009 on total investment for the treated firms. The figure is calculated by regressing the total investment on year and year-treatment dummies. The year is normalised in the graphs to be relative to the treatment year.

Figure A6: IT Investment, 2009 AIA change



Notes: The figure illustrates the relationship between the introduction of the AIA in 2009 on 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 A7: IT Hardware Investment, 2009 AIA change



Notes: The figure illustrates the relationship between the introduction of the AIA in 2009 on IT 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.