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Evidence on Cloud, Big Data and AI

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Abstract

The arrival of cloud computing provides firms a new way to access digital technologies as digital services. Yet, capital incentive policies present in every OECD country are still targeted towards investments in information technology (IT) capital. If cloud services are partial substitutes for IT investments, the presence of capital incentive policies may unintentionally discourage the adoption of cloud and technologies that rely on the cloud, such as artificial intelligence (AI) and big data analytics. This paper exploits a tax incentive in the UK for capital investment as a quasi-natural experiment to examine the impact on firm adoption of cloud computing, big data analytics and AI. The empirical results find that the policy increased investment in IT capital as would be expected; but it slowed firm adoption of cloud, big data and AI. Matched employer-employee data shows that the policy also led firms to reduce their demand for workers that perform data analytics, but not other types of workers.

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Do Capital Incentives Distort Technology Diffusion? Evidence on Cloud, Big Data and AI

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1 Introduction

Policy tools have long been used to shape production technology. These include incentives for particular outputs, such as innovation or exports, or the use of particular inputs, like local sourcing or capital investment (Juhasz et al., 2023).[1] Once enacted, such policies tend to persist (Bonomo et al., 2015), which can have unintended consequences for the path of technological change. For instance, lower taxes on capital (relative to labor income) may have accelerated the diffusion of labor-saving automation in the US (Acemoglu et al., 2020).

Historically, most firms acquired new technologies through purchases of capital, including in the last half century computers and servers (Comin and Hobijn, 2010; Jones and Liu, 2022). Differences in these investment paths across countries can help to explain diverging development trends since the start of the industrial revolution (Comin and Mestieri, 2018; Collins et al., 1996; Krugman, 1994). To encourage such investments and spur growth, policy makers frequently use capital incentive programs, which work by reducing the cost of capital (Jorgenson, 1963; Hall and Jorgenson, 1967). Today, such policies are in place in every OECD country, whether it be in the form of tax allowances, subsidies or grants (Tax Foundation, 2018). Overwhelming empirical evidence points to their effectiveness (Cummins et al., 1994; House and Shapiro, 2008; Zwick and Mahon, 2017; Ohrn, 2018; Maffini et al., 2019).[2]

Following the launch of Amazon Web Services in 2006, firms are now also able to acquire data storage, computing and software services through the cloud, allowing them to substitute away from upfront investments in tangible digital technologies (DeStefano et al., 2023; OECD, 2014). Firms can rent a server from a cloud provider for example, rather than buying it. The growth of this new way of accessing information technology (IT) has been rapid, with expenditure on cloud services comprising 25% of European firms' IT budgets in

[1]These industrial policies are attracting attention in view of the need to shift towards low-carbon production technologies (European Commission, 2023).

[2]Often these are targeted at financially constrained firms, such as SMEs. Again, the empirical evidence points to particularly strong responses from these groups of firms.

2016 (Van Ark, 2016; OECD, 2017; Eurostat, 2018). Growth in cloud use has been driven by supply-side cost reductions, as cloud providers take advantage of economies of scale in computing, with giant data centers comprised of hundreds of thousands of servers (Greenstein and Fang, 2020), and demand side pull that follows from the ability of firms to scale their digital needs flexibly on demand (DeStefano et al., 2023).[3]

Digital services are, however, typically outside the scope of capital incentive programs. This raises a question of whether these policies distort a firm's choice of investing in tangible IT capital versus purchasing cloud computing services. Since earlier technological vintages can be important for the path of future technology use (Jovanovic and Lach, 1989; Atkeson and Kehoe, 2007; Comin and Hobijn, 2010; Jovanovic and Yatsenko, 2012), it raises a more important question as to whether capital incentives affect the diffusion of data technologies complementary to cloud services, notably big data analytics and AI. These technologies have been identified as possible general purpose technologies, such that the answers to these questions has potential widespread implications for future employment growth, innovation and productivity (Brynjolfsson and McAfee, 2014; Goldfarb et al., 2023).

The effect of capital incentives on big data analytics and artificial intelligence (AI) depends on the extent to which firms can use their own IT capital, or rather, whether there are advantages to using cloud computing. On the one hand, if capital incentives increase investment in IT hardware to store and process data, then this may encourage the adoption of big data analytics and AI. On the other hand, if cloud computing is strongly complementary to the use of big data and AI, then capital incentive policies (by slowing cloud diffusion) may also slow adoption of these technologies. Brown et al. (2011), Goldfarb et al. (2023) and DeStefano et al. (2023) offer the argument that the ability of cloud services to be flexibly scaled up and down on demand gives reason to expect that technologies that are data intensive may be stronger complements to cloud services.

[3]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 (Lesser, 2017). By 2016, it is calculated that 30% of firms used cloud across the OECD (Eurostat, 2018).

This paper presents the first evidence of whether capital incentives distort recent technology diffusion - using the cloud versus own IT investment as an example. We employ novel firm-level panel data which captures the adoption of cloud, big-data analytics and AI, along with traditional investments in tangible capital, including total IT investment, as well as hardware and software.[4] In addition, we use matched employer-employee panel data to measure the demand for data analytics workers - as an alternative proxy for technology adoption following Corrado et al. (2022).[5] If the AIA policy affects firm adoption of data analytics technologies, such as cloud, big data analytics or AI, then one would expect that this would also materialise in the demand for workers performing data analytics tasks.

We study capital investment and technology diffusion in the setting of a quasi-natural experiment that exploits the introduction and adjustments to the eligibility threshold for a capital incentive policy in the UK, the Annual Investment Allowance (AIA). This scheme allowed firms to deduct the cost of investment in capital (including IT capital) against profits up to a threshold value of profits, where this threshold was adjusted over time.[6] The AIA impacted the marginal investment cost of some firms and not others, allowing us to use a difference-in-differences approach comparing treated versus control firms.[7]

As firms can adjust their investment in response to the AIA, this poses a potential selection problem - firms may limit their investment in a given year to stay below the AIA incentive thresholds. To address this issue, we follow the empirical approach of Bjuggren (2018), Saez et al. (2019) and Bøler et al. (2015). These papers examine the effects of employment protection legislation or R&D tax credits in settings that also feature changes

[4]We note that software is considered an intangible asset, but was nonetheless eligible for the AIA policy in addition to conventional tangible assets, as discussed in section 2

[5]Corrado et al. (2022) use changes in employment of occupations that perform data tasks to construct economy-level time series of data investments. In our context we use changes in demand for occupations that perform data tasks as a measure of diffusion of firm-level data technologies.

[6]As noted earlier, cloud computing expenditures are not eligible for the incentive.

[7]The introduction of the AIA will of course have affected the average tax rate for both treatment and control firms. However, 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 encourage the use of new capital" (p. 30), indicating that it is the marginal rate that is relevant here. That the change in the marginal tax rate is zero for firms above the capital investment threshold explains why we do not use a regression kink design (Card et al., 2015).

in qualifying thresholds. Similar to these studies, we define firms' treatment status using their historic values of the endogenous variable, in our setting their (pre-AIA) capital investments, which we compare to (future) AIA tax-allowance thresholds.[8] In this way we obtain reduced firm estimates of the intention to treat effects of this tax policy on cloud, big data analytics and AI adoption.[9]

Our empirical results show that for those firms for whom the marginal cost of capital fell due to AIA threshold increases, there were large increases in tangible capital investment. Among treated firms, total capital investment rose by an estimated 61.7% between 2007 and 2013, with similar strong effects apparent up to the end of our data period in 2019. However, for these same firms, the AIA reduced their adoption of cloud technologies. Our results therefore confirm that the capital incentive did distort technology diffusion. Cloud adoption was 17 percentage points lower for firms eligible for the AIA, compared to a mean rate of cloud adoption of 28% over the same period. The negative effects of the capital incentive program are also found to be stronger for cloud data and storage services – those related to the storage and processing of data – than compared to accessing office and finance software or email through the cloud. Some back of the envelope estimates of the aggregate impact suggest that the policy reduced overall cloud use in the UK by between 7-9 percentage points, or equivalently, the AIA slowed cloud diffusion by more than one year.

We find that SMEs respond particularly strongly to the AIA compared to large firms. The estimates suggest that SMEs eligible for the AIA are 37% less likely to adopt cloud technologies. Earlier research suggests smaller firms benefit most from the cloud (through

[8] Recognizing that there may be adjustment costs in reaching the desired capital stock for the firm (Chirinko, 1993), in our baseline estimations we average capital investment across time.

[9] As explained in the data section of the paper, the data on capital investment is available at a higher time frequency (annual) than the firm-level data on the digital technologies such as cloud, big data and AI. To account for the staggered treatment design features of the AIA, in the regressions for capital investment we rely on Callaway and Sant'Anna (2021). These staggered treatment estimation methods are not possible with highly unbalanced panels, so for the digital technology variables we use long-difference regressions. Our results are also robust to using long-difference specifications throughout. However, our additional proxy for technology adoption, the demand for workers that perform data analytics uses annual data, which we estimate following Callaway and Sant'Anna (2021). We return to this point in more detail in Section 4.

the flexible/variable costs it provides),[10] and yet we find these are precisely the firms for which diffusion is slowed most by the capital incentive.

Moving to the impact of capital incentives on other data technologies, we find evidence that the AIA policy also lowered the likelihood of using big data analytics and AI, by 18% and 3%, respectively, among treated firms. For these technologies, back of the envelope estimates suggest an aggregate slowdown in big data and AI use in the UK of 7 and 1 percentage points. While seemingly small, the slowdown is large compared to the level of big data and AI use in the UK - slowing their diffusion between one and two years. We estimate the use of big data would have been 14% higher and AI 30% higher in the absence of the distortion created by the AIA. These findings are consistent with cloud computing being complementary to big data and AI.

These results are further supported by the worker-level analysis, which shows that firms treated by the AIA policy reduced the wages of workers in occupations that perform data analytics by approximately 1.1% compared to non-treated firms. Reassuringly, we do not find an impact of the policy on other types of workers within the same firms, such as those that do not perform data tasks or those working on database creation. Thus, we do not see that the AIA affects labor demand in general, but rather slows demand for data analytics occupations, consistent with our firm-level results above.

The results remain unchanged under various robustness tests, including how we measure treated firms using historical investment data, consideration of other potentially confounding policy changes, the exclusion of larger firms that might be expected to adopt newer IT technologies more readily, exclusion of smaller firms and the addition of controls that account for different trends in the rate of digital technology adoption by firms of different sizes or different industries.

This paper primarily contributes to the literature on the path-dependencies in technology diffusion and how policy can be used to direct technological change. The direction of

[10] See for instance Jin and McElheran (2017); DeStefano et al. (2023).

technological change exhibits path-dependency because new technologies often build on prior experience or share prerequisites (Acemoglu et al., 2012; Aghion et al., 2016). Policy can play an important role in redirecting technological change where the market outcome is not socially optimal, e.g. carbon-intensive or labor-replacing technology (Aghion et al., 2016; Hémous and Olsen, 2021; Acemoglu, 2023).[11] This literature has also shown that temporary policies can have long-term impacts on technology use, such as temporary restrictions on foreign competition during the Napoleonic war and the diffusion of cotton spinning, or say temporary input cost advantages and the transition from wooden to metal shipbuilding (Juhasz, 2018; Hanlon, 2019). We add to this literature by showing that capital incentive policies can inadvertently affect the direction of technological adoption in ways that are at odds with their overall objectives.

A second literature examines the diffusion and performance effects of data technologies. The value of data assets in 9 European countries, measured by the wages of occupations that perform data tasks, increased by more than 40% between 2010 and 2019 (Corrado et al., 2022). In US manufacturing for example, the use of data-driven decision making nearly tripled from 11% to 30% between 2005 and 2010 (Brynjolfsson and McElheran, 2016). In the EU, the use of big data analytics by firms expanded from 9% to 14% between 2015 and 2019 and the use of AI reached 6% by 2020 (OECD, 2023). Cloud computing appears to be an important driver for the adoption of big data and AI (Cho et al., 2023; DeStefano et al., 2023; Zolas et al., 2020) as it lowers the cost of collecting, storing and processing large amounts of information (Brown et al., 2011). Adoption of these data technologies has been linked to a variety of firm performance gains, including productivity, innovation and employment (Brynjolfsson and McElheran, 2016; Niebel, 2018; Koning et al., 2022). Policies that discourage the use of cloud services and thus big data and AI, have further importance if they hinder current and future competitiveness at the micro-level and aggregate growth at the macro level.

[11] This fits into a broader debate about the merits of capital incentives or alternative types of policy around innovation (Mazzucato, 2017; Bloom et al., 2013; Howell, 2017; Bloom et al., 2019).

Finally, we contribute further evidence to the literature on the effects of tax incentives on the capital investment subsidized by these policies. Within this literature, House and Shapiro (2008), Ohrn (2018) and Zwick and Mahon (2017) have all shown how tax policy, such as accelerated depreciation, can stimulate firm investment by reducing the cost of capital. For the UK, Maffini et al. (2019) examine the impact of an earlier accelerated depreciation policy on capital investment, also using changes in qualification thresholds to identify causal effects as we do in this paper.[12] Also for the UK, Gaggl and Wright (2017) examine the impact of a short-lived tax allowance on IT investment available to small firms on IT investment and employment. In this paper we first examine the impact of this particular program on investment, the intention of the policy, but distinguish from the above papers by also considering the broader unintended impacts on technology adoption.

The rest of the paper continues as follows: Section 2 presents details on the AIA policy, Section 3 describes the data and Section 4 lays out our estimation strategy. Section 5 presents the main results of the paper while Section 6 summarizes the results and provides some policy discussion.

2 The Annual Investment Allowance Policy

The Annual Investment Allowance was introduced in the UK for the financial year (April) 2008-2009, with the objective of stimulating firms to invest in new forms of tangible capital and thereby encouraging economic growth (HMRC, 2018).[13] The scheme allowed firms to deduct during their accounting year their capital investment from their pre-tax profits up to a profit ceiling. As we discuss below, this ceiling has shifted a number of times over the sample period. The AIA incentive covered all long-term equipment used to produce or

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

[13]The AIA was seen as a movement within UK tax policy away from a size or legal form linked incentive, towards one targeting investment (Crawford and Freedman, 2010). We consider earlier incentive schemes later in this section.

sell products – termed "plant and machinery" – which includes IT capital. Other types of capital, such as land and buildings, were not eligible for the allowance, which we use later as a test of the validity of our empirical approach.[14]

The AIA scheme was first mentioned in a March 2007 budget press notice one year prior to the start of the new allowance.[15] The policy appears to have been unanticipated before that point, with contemporaneous news headlines of the type "Budget 2007: Surprise overhaul announced for capital allowances from 2008".[16] As discussed later, we use firm investment in years prior to this announcement to determine our treatment and control groups.

Since its introduction, the AIA investment ceiling has changed many times. The initial ceiling for the financial year ending April 2009 was set at £50,000. In March 2010 it was announced this would increase to £100,000. A change in government then occurred in May of that year, and following a special budget in June 2010, it was announced the AIA ceiling would subsequently be cut to £25,000, effective from April 2012. This new lower threshold was in place for a period of only 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). The time period for this temporary increase was extended until January 2016 and at the same time the ceiling increased further to £500,000 in the 2014 Budget. A further demonstration of the uncertainty over the direction of future changes in this allowance is highlighted by noting that the 2015 election manifesto by the Conservative Party, which had formed the incumbent ruling party, 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. In the 2015 Budget, the AIA was set to a "permanent" level of £200,000 (to start from January 2016). In the 2018 Budget it was announced this would increase to £1 million from January 2019.

[14] A list of eligible and ineligible capital expenditure is contained here https://www.gov.uk/capital-allowances/what-you-can-claim-on

[15] Treasury (2007) – Press Notice 1.

[16] Available at https://www.accountingweb.co.uk/tax/hmrc-policy/budget-2007-surprise-overhaul-announced-for-capital-allowances-from-2008.

Table 1: Annual Investment Allowance Ceiling, 2008 to 2015

	AIA Ceiling
March 2008 and before	-
April 2008 – March 2010	£50,000
April 2010 - March 2012	£100,000
April 2012 - December 2012	£25,000
January 2013 - March 2014	£250,000
April 2014 - December 2015	£500,000
January 2016 - December 2018	£200,000
January 2019 onwards	£1,000,000

Source: https://www.gov.uk/capital-allowances/annual-investment-allowance

Not surprisingly, this approach to tax policy has been much criticized within the economic community (Miller and Pope, 2015).[17] The timing of these changes are summarized in Table 1.

A-priori it would be expected that physical IT capital investment and cloud adoption would respond differently 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 the cost of capital. The increase in the AIA threshold lowered the cost of capital for some businesses, encouraging new investment. Harper and Liu (2013) calculate for example, and assuming a March financial year-end for firms, that following the 2010 increase in the AIA ceiling from £50,000 to £100,000, the cost of capital for an additional £1 investment between these two figures decreased by 28% if financed by retained earnings or equity, and by 31% if financed with debt. These are large changes. The authors also note that if internal financing is less costly than external financing, the AIA would have further positive effects on investment spending for financially constrained firms. Increases in the allowance over time should therefore increase the incentives for firms to invest in their own physical IT capital, compared to purchasing these IT storage and computing services via the

[17] 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.

cloud.

Several further details about the AIA allowance will be important for the later empirical analysis. Firstly, the available allowance to any given firm in any given year depends on the timing of their financial year end.[18] For instance, firms with a financial year ending March 2010 would be eligible for an allowance of £50,000. However, firms with a financial year ending December 2010 would receive an allowance of £87,500, since they incur 3 months of the £50,000 allowance (until March 2010) and the remaining 9 months of the £100,000 allowance (from April 2010). About half of firms have a December (53%) year end in our data, while a further 16% have a March year end, with the remainder distributed fairly evenly among the remaining months. We use rich information in our data on the date of each firm's financial year end to calculate the AIA ceiling specific to each firm for a given year. This ensures that the capital allowance available to a firm matches the frequency with which their investment and digital technology use are reported in the data.[19]

Secondly, the effects of capital investment programs also depend on expectations of the future. As already mentioned, throughout the life of the policy (2008-2019), the AIA ceilings changed a number of times. These changes often occurred unexpectedly, and were sometimes announced as being only temporary. As noted earlier, the initial policy introduction also appears to have been unanticipated. As such, the policy changes present an ideal context for the assessment of its impact.

Finally, while the introduction and changes to the AIA are expected to influence firm investment decisions, it is important to identify the presence of other policies during our sample period which may confound the results. We have identified two of interest. One potential policy was the First Year Allowance (FYA). The FYA was also a capital investment program introduced before our sample period and then ended in 2008, making a reappearance in 2010 for one year. This policy was similar to the AIA in that it provided tax allowances

[18] See https://www.gov.uk/capital-allowances/annual-investment-allowance

[19] Although cloud providers themselves would also in principle be eligible for the AIA incentive, the tax incentive applies to investments up to the threshold, which are many orders smaller than the scale of cloud provider investments in data centers and the like.

for investments in physical capital, but were targeted at small firms with revenue below £22.8 million.[20] To ensure that our results are only capturing the effects of the AIA, and not any residual impacts of the FYA, as a robustness test we exclude firms in our sample with revenue below the threshold necessary to qualify for the FYA.

A second policy of interest was an alteration to the definition of SMEs by the EU in 2008 which in turn affected qualification for the R&D Tax Relief Scheme for UK firms. This definition change shifted the qualifying threshold of assets from €43 million to €86 million, the employment threshold from 249 to 499, and the sales threshold from €50 million to €100 million (Dechezleprêtre et al., 2016). Again, we explore the robustness of our findings to the exclusion of firms that become eligible for the R&D incentive.[21]

3 Data and summary statistics

The research relies on four types of data: panel data on firm use of cloud, big data and AI technologies; matched employer-employee data; details regarding the introduction and changes to the AIA; and firm capital investment data.

All firm level data are taken from the Office for National Statistics (ONS), which is the UK's Census Bureau equivalent. Information on cloud, big data analytics and AI adoption is available through the E-commerce Survey. The survey contains questions on firm use of different types of cloud computing, including its use for hardware services such as data, storage, processing, and software services, such as finance software, office software, customer relationship management software and email. We code the firm as an adopter of cloud technologies if it uses any of these different cloud services and zero otherwise.

The survey also includes questions on the use of big data analytics and AI. We construct a measure of firm use of big data as a binary variable which is equal to 1 if an enterprise

[20] See Maffini et al. (2019) for further discussions on the FYA.

[21] During our sample period the UK did not have any policies that were specifically targeted at digital technologies beyond the AIA. A capital incentive scheme targeting IT investment by small businesses was in place between 1st April 2000 to 31st March 2004 which was empirically investigated by Gaggl and Wright (2017).

reports that it analyzes big data via either of the following methods: the enterprise's own data collected with smart devices or sensors, data gathered from geolocation data from the use of portable devices, generated from social media, and data collected from other external sources.[22] The E-commerce survey includes information on two separate measures of AI technologies, notably machine learning and natural language processing. Similar to the construction of the other technology variables, we create a binary variable equal to 1 for firms using AI in either of these forms and zero otherwise.

The matched employer-employee data comes from the Annual Survey of Hours and Earnings, provided by the ONS, and comprises panel data on the wages of 1% of UK workers. Since the data is a sample of workers, this prevents us aggregating to the firm-level, and limits us to worker-level analysis. We examine the demand for workers that perform data analytics (or business intelligence) tasks , those that perform other data tasks (specifically, database, data stores or software creation) and those that do not perform data tasks, using occupation information on time use from Corrado et al. (2022).[23]

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, eligible investment, when the policy was introduced (2008) and details on changes in the thresholds over time up to 2019. Measures of IT capital investment, as well as historic (pre-AIA) total investment in plant and machinery and the date of each firm's financial year end – which we use to identify our set of treated firms – are taken from the Annual Business Survey (provided by the ONS). Finally, data on firm control variables, age, multi-establishment status and foreign ownership are sourced from the UK business registry – the annual Business Structure Database.

[22]The E-commerce survey defines big data and big data analytics as the following. Big data typically have characteristics such as: (1) vast amounts of data generated over time, (2) variety in terms of different formats of complex data, either structured or unstructured (for example text, video, images, voice, docs, sensor data, activity logs, click streams, coordinates). (3) velocity in terms of the high speed at which data are generated, become available and change over time. Big data analysis refers to the use of techniques, technologies and software tools for analyzing big data from our own business or other data sources.

[23]Given that half of workers do not spend any time on data tasks, see Table A2, we use non-zero time use on data tasks to determine these groups

Our baseline sample period focuses on the effects of the earlier years of the AIA from 2007 to 2013 for total investment and cloud. The year 2013 is chosen as this is the first time for which questions on cloud use were included in the E-commerce survey. We assume zero adoption for all firms in 2007, consistent with the assumption of DeStefano et al. (2023), as this is before cloud computing arrived in the UK. In the robustness section we test for the use of the other time periods for which information on cloud use by firms is available, namely 2015, 2017 and 2019. Information on the use of big data analytics are collected for the years 2015 and 2019 and for AI in the year 2019. Again we assume zero adoption in 2007 for both. Worker-level estimation of the demand for data workers and total investment at the firm level takes advantage of annual data for the years 2007 to 2013 and 2007 to 2019 (inclusive).

Table 2 below provides summary statistics of the main variables and time periods we use in the main body of the paper. For the period up to 2013 our data show that 28% of firms in our sample use cloud, but that this varies across types of cloud service. For example, only 6% of firms use cloud for finance software, whereas 16% use cloud for storage of files. For big data analytics, 21% of firms use big data by 2015 (26% in 2019), while only 1.7% of firms use AI by 2019. Additional summary statistics for all firm variables for all time periods are available in Table A1, and worker summary statistics are in Table A2.

4 Empirical strategy

To identify the effect of the AIA capital allowances on capital investment, cloud technologies, big data and AI we use a difference-in-differences (DID) specification with some minor distinctions discussed below depending on whether we model IT investment (available annually) or the technology variables (available in specific years). The structure of the difference-in-difference regressions measure the outcome of firm i in period t before and after AIA, the introduction of the AIA allowance relative to the control group expressed as follows, where Z_{it}

Table 2: Firm Descriptive statistics

Variables	Mean	SD	Observations	Sample coverage
Annual Investment Allowance				
AIA dummy	0.095	0.294	25,117	(2007-2013)
AIA available allowance	0.007	0.030	25,117	(2007-2013)
Firm investments (logs)				
Total investment	6.598	2.334	24,467	(2007-2013)
Software investment	2.412	2.592	24,467	(2007-2013)
Hardware investment	3.764	2.592	17,985	(2007-2013)
Plant-Machinery investment	5.866	2.409	22,976	(2007-2013)
Vehicles investment	3.358	2.195	19,097	(2007-2013)
Land-Building investment	1.198	2.498	22,587	(2007-2013)
Firm technology adoption				
Cloud	0.281	0.449	2,206	(2007 & 2013)
Cloud Storage	0.157	0.364	2,206	(2007 & 2013)
Cloud Data	0.126	0.364	2,206	(2007 & 2013)
Cloud CRM	0.09	0.286	5,084	(2007 & 2013)
Cloud Finance software	0.055	0.228	2,206	(2007 & 2013)
Cloud Office software	0.068	0.252	2,206	(2007 & 2013)
Cloud Email	0.12	0.325	2,206	(2007 & 2013)
Cloud Own Software	0.072	0.403	2,206	(2007 & 2013)
Big data analytics	0.205	0.404	2,264	(2007 & 2015)
Big data analytics	0.259	0.44	1,748	(2007 & 2019)
Artificial Intelligence	0.017	0.13	1,748	(2007 & 2019)
Control variables				
Multi-establishment	0.751	0.433	24,467	(2007-2019)
Foreign owned	0.330	0.470	24,467	(2007-2019)
Age (log)	3.304	0.400	24,467	(2007-2019)
Employment (log)	6.132	1.578	23,467	(2007-2019)

Note: All investment variables are in log thousands of UK pounds, deflated using 4 digit (2007 SIC codes) PPI deflators provided by the ONS. The AIA available allowance is in (nominal) millions of UK pounds.

takes the value one for the treatment group in the post-treatment period and zero otherwise:

$$y_{it} = \alpha + \beta Z_{it} + FE_i + FE_t + \chi_{it} + \epsilon_{it} \tag{1}$$

In Equation (1) the estimated coefficient β is the difference-in-difference parameter of interest. 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 age, multi-establishment status, foreign ownership and lagged employment.[24] Our baseline period focuses on the earlier years of the AIA from 2007 to 2013, which corresponds to the year before the AIA as launched and the first year data was collected on cloud.[25]

If the AIA policy affects firm adoption of data-analytics technologies, such as cloud, big data analytics or AI, then one would expect that this would also materialise in the demand for workers performing data-analytics tasks. The worker-level estimation employs a similar annual difference-in-differences (DID) specification to the investment regressions above. It estimates the wages of worker w connected to firm i in period t before and after AIA treatment Z_{it}. We estimate Equation 1 separately for data analytics workers, other data workers and the remaining (non-data) workers. Thus we are comparing the demand for data analytics workers in firms treated by the AIA compared the data analytics workers in non-treated firms:

$$y_{wit} = \alpha + \beta Z_{it} + FE_w + FE_t + \phi_{wt} + \chi_{it} + \epsilon_{it} \tag{2}$$

We include worker and year fixed effects, to control for slow-moving unobserved worker factors and common trends, reflected by FE_w and FE_t respectively. To control for potential

[24]The exclusion of these controls does not alter the results and has almost no impact on the magnitude of the estimated coefficients in the baseline regressions.

[25]In the robustness section we test for the use of the other time periods for which information on cloud use by firms is available, namely 2015, 2017 and 2019. We also include these later years when examining the effects of AIA on big data and AI adoption.

sorting, we follow the literature and include a vector of worker controls ϕ_{wt}, including age, tenure, tenure squared, skilled occupation dummy, gender and the interactions of the other worker controls with gender. χ_{it} is a vector of firm control variables as above. We find few cases of workers switching into or out of data occupations, and results are robust to their exclusion.[26]

We use changes in the AIA as a quasi-natural experiment to identify a set of treated firms for whom the marginal incentives to invest (in capital) fell. To identify treated firms, we first calculate the average value of acquisitions of tangible capital by the firm prior to the announcement of the AIA (following the R&D incentive literature, such as Bjuggren (2018); Saez et al. (2019); Bøler et al. (2015)). As investment values can be lumpy (Chirinko, 1993; Maffini et al., 2019), we calculate this as the average across the years 2005 and 2006. We avoid using the year 2007 as the AIA policy was first announced in a press release in March of that year, although the results are unchanged if we include data from that year alongside those from 2005 and 2006. It follows from the use of historic firm investment that we are capturing "intention to treat" estimates through Equation (1), that is, those whose historic investment would predict treatment at the time of the policy change.

Firms receive the incentive on investment up to an allowance ceiling that varies according to their year end, as noted in the previous section of the paper. This necessitates the construction of a treatment variable that captures this. To give an example: assuming for the moment that the accounting year-end of the firm is the end of March, a firm with an average investment of £75,000 across 2005 and 2006 would be above the AIA ceiling in 2010 (AIA ceiling of £50,000) and therefore coded as zero (our control group), but in 2011 this firm's lagged investment would be beneath the threshold of £100,000 and therefore coded as one in that year (our treatment group). As noted in the previous section, we calculate these binary values each year using each firm's allowance ceiling, based on the date of their

[26] For example, between 2007 and 2019 there are only 9,953 observations relating to workers switching into or out of data analytics occupations, compared to a total of 455,069 worker observations, noted in Table A2. The results are also robust to the switching of workers between firms and the exclusion of these movers.

accounting year-end.

As an extension, rather than a binary treatment variable, we also calculate a continuous measure reflecting the number of pounds the firm is below the AIA ceiling. The intuition being that firms with more unspent allowance, have a greater incentive to increase their investment. We use this continuous measure of the AIA allowance available to firms as a robustness test below. That the magnitude of the response to the AIA policy is likely to increase with the gap between a firms historical capital investments and the AIA threshold also helps to provide an argument for why the DID approach adopted in the paper is preferable to, for example, a regression discontinuity (RD) design. An RD design would measure the effects of the AIA for firms around the threshold, thereby ignoring those for which the change in the AIA threshold is most significant.[27]

We note some differences in the specification when using the capital investment or worker data and that on cloud, big data and AI. When studying the effects of AIA on capital investment or demand for data workers this data is available on an annual basis and therefore the treatment status of the firm is determined by these annual changes in the marginal incentive to invest by year. The presence of firm/worker and year fixed effects in Equations 1 and 2 along with the changes to the AIA policy across years means the regression belongs to the two-way fixed effects models with staggered treatment design that has received much recent criticism about 'forbidden comparisons', i.e. comparing treated firms to previously treated firms as well as those not treated (Goodman-Bacon, 2021; Borusyak et al., 2021; Callaway and Sant'Anna, 2021). As our preferred method, we use the approach of Callaway and Sant'Anna (2021), which accounts for staggered treatment designs and heterogeneous treatment effects under semi-balanced panel data. The approach presents event study estimates of investment of treated firms (for each cohort of AIA changes), by comparing against those firms that are never treated and not yet treated as a control group.[28] We also examine

[27]We are not able to estimate a regression kink design due to relatively small samples for our technology regressions.

[28]The results are similar if we only use never treated firms as controls.

robustness to long-difference estimation, comparing investment in a future period to the year before the AIA policy, which also removes any previously treated firms by definition.

The measures of cloud, big data and AI are available only for a few specific years, so we estimate as long-differences, comparing technology adoption in a future period to the year before the AIA policy. When exploring these outcome variables our treatment is then determined as those firms for whom the marginal incentives to invest (in capital) fell at some point between the start of the AIA (in 2007) and the given future period (2013/15/17/19 depending on available digital technology measure), while control firms are firms who marginal incentive to invest did not change over this period. We do this by measuring treatment status as the maximum of the year-by-year treatment dummies described above - i.e. firms that were treated in any year. For the continuous measure we construct the mean value over the years between 2007 and the given future period (2013/15/17/19). Finally, we note that as we measure outcomes only in a single pre-treatment period and a single post-treatment period concerns over staggered treatment does not apply and we can estimate Equation 1 using OLS.[29]

The validity of difference-in-differences rests on parallel trends in the absence of treatment. We follow common practice in the literature and test this by comparing the treatment and control groups in the periods before treatment takes place. To do so we show graphically how the treatment effects of changes in the AIA evolves over time using the approach of Callaway and Sant'Anna (2021). For completeness, we note that such test for pre-trends is not possible for the firm digital technologies as they had not been invented by the start of the AIA policy.

In Figure 1, we present the event study plot for total investment against its associated treatment-year dummies. It is clear that in the periods leading up to the different AIA changes, the treatment and control groups share similar pre-treatment trends. There is a

[29]With few periods, the degree of the treatment stagger is inherently limited, and in any case, without a semi-balanced panel it is not possible to employ new staggered treatment estimators, such as Callaway and Sant'Anna (2021).

large increase in investment by treated firms in the post-treatment period (consistent with the later results in Table 3 below). This effect is apparent in the year in which the marginal incentive for the firm changes, consistent with the ambitions of the AIA policy, and continues in the five years post-treatment. Our event study plots are robust to alternative similar definitions of firms' treatment status based on their historic investment.[30] For example, Figure A1 uses 2-year average investment data for the years 2006/07 while Figure A2 uses 3-year averages for the years 2005/06/07.

As a further check on the parallel trends assumption, we similarly examine the pre-treatment trends for the wages of data analytics workers (Figure A3), exploiting that these are measured on an annual basis. In the periods before the AIA changes we do not observe a differential trend in wages of data analytics workers between the treated and control firms (although the worker-level estimation is somewhat more noisy than the preceding firm-level plots). Around two years after treatment we observe a decline in the wages at treated firms, mirroring later results in Table 6. These results are consistent with the existing literature which finds both that technology adoption is linked with subsequent labor demand (Bresnahan et al., 2002) but that this organizational change occurs overtime (Juhász et al., 2020).

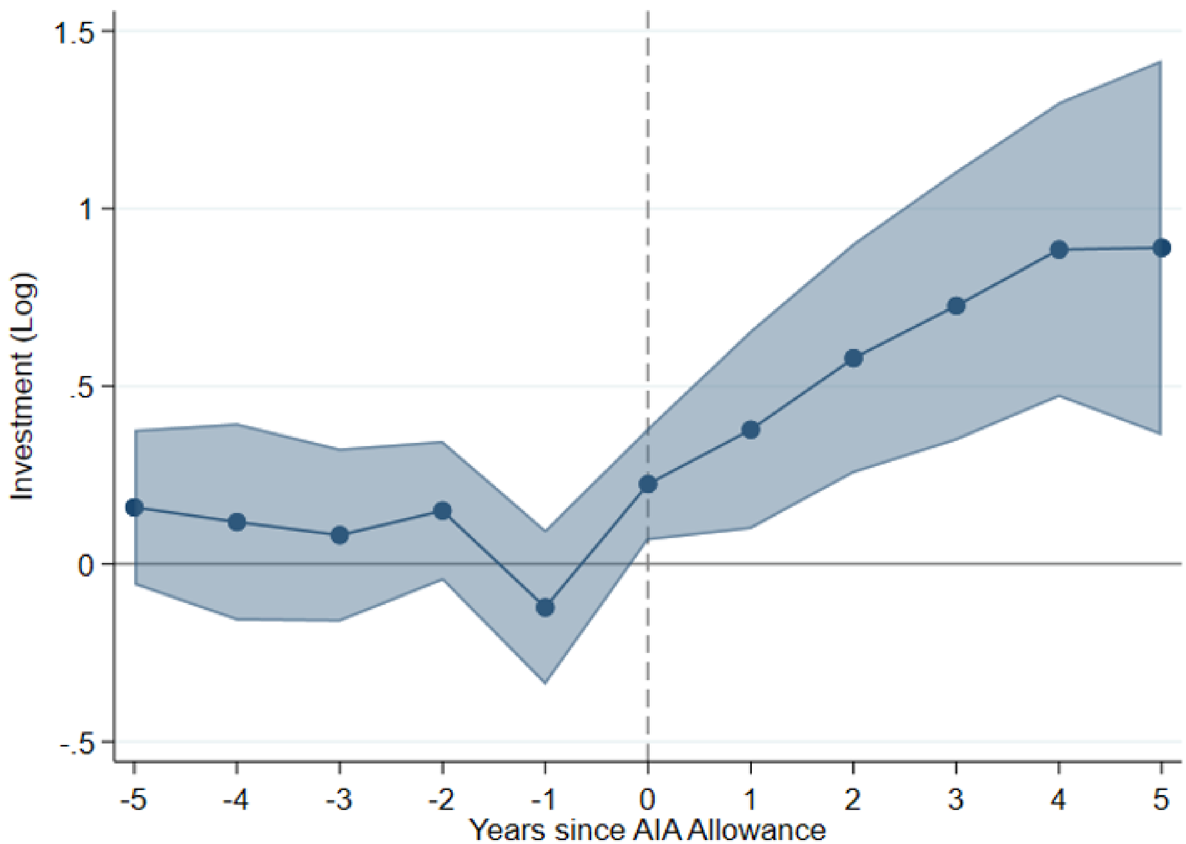
5 Results

5.1 The effects of AIA on cloud and capital investment, 2007-13

This section examines econometrically the treatment effect of changes in the AIA allowance on firm investment in IT capital and cloud adoption. The AIA was designed and implemented by policy makers with the objective to increase physical capital investment, including the stock of digital technologies through investments in traditional tangible IT capital. We find evidence that the policy was successful in this regard. The results in Table 3 find that firms

[30] The absence of pre-trends is also apparent if we estimate these regressions over the period to 2019.

Figure 1: Total investment and years pre and post the AIA allowance



Notes: Data period: 2007-2013. The above figure presents the coefficients and 95 per cent confidence intervals of event study regressions – reflecting firm total investment in the periods before and after changes in the AIA threshold. The threshold is calculated using 2-year average investment in years 2005/2006. Event time is equal to 0, the preceding year is event time of –1, the year after the event is +1, and so on. The estimation follows the method of Callaway and Sant'Anna (2021), see Equation 1.

who became eligible for the AIA increased total investment.[31] In terms of the economic magnitude the coefficient from column 1 suggests that the policy on treated firms leads to an increase in total investment by 61.7% over the period 2007 to 2013.[32]

As shown in Tables A3 and A4 these results for investment are robust to a number of changes in sample period or years over which eligibility for the AIA is calculated. In Table A3, we show results for investment for the years up to 2015 (regression 1), 2017 (regression

[31]The absence of firm balance sheet data prevents analysis of the user cost of capital or financing.

[32]Since the investment outcomes are in logs, the percentage increase in total investment is calculated as 61.7% = exp(0.481)-1.

2) and 2019 (regression 3). Relying on the same years in which data is available for cloud and using its same long differences specification, also leads to consistent results (regression 4). In Table A4 we show the effect of the AIA on investment holds irrespective of whether we define the treatment status of the firm using a 2-year average based on the years 2006/07 (regression 1), or a 3-year average based on the years 2005/06/07 (regression 3).

In contrast to its effects on investment, AIA eligibility reduces the propensity to adopt cloud, in this case by 16.5 percentage points. The magnitude of the estimated coefficient is relatively large compared to the mean rate of cloud adoption, of 28% 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 services and towards tangible IT investment.

Table 3: Effects of AIA on total capital investment and cloud adoption, 2007-2013

Regressions	(1)	(2)
Dependent variable	Total Investment	Cloud
AIA Dummy	0.481***	-0.165***
	(0.105)	(0.040)
Observations	21,757	2,200

Note: Time period: Total investment regressions use annual data for the years 2007 to 2013. Cloud regressions use data for 2007 and 2013. Total investment is in (log) thousands of pounds, while cloud is a dummy variable. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. Regressions use a binary AIA eligibility indicator. Regression 1 is estimated using the method outlined in Callaway and Sant'Anna (2021) and regression 2 uses OLS. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age. These are not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

To give a sense of the aggregate slowdown in cloud use induced by the AIA policy, we repeat our baseline estimation applying sampling weights.[33] The weighted regressions show

[33] These aggregate estimates are approximate as they do not account for general equilibrium effects, and some sectors and firms with fewer than 10 employees are not surveyed in our data. The results are available

similar coefficients to our baseline, the AIA policy reduced cloud use for treated firms by between 15-20 percentage points (depending upon estimation period, 2007-2013 or 2007-2019). Since around 43%-46% of firms were treated by the AIA policy, this implies an aggregate reduction in cloud use of 7-9 percentage points. Over our sample period aggregate cloud use has been increasing roughly 6 percentage points per year (whether measured over 2007-2013 or 2007-2019). Thus, the AIA policy appears to have slowed down cloud diffusion by 1 to 1.2 years.

Again we note the robustness of these results if we define firms' treatment status using a 2-year average of investment based on the years 2006/07 (regression 2), or a 3-year average based on the years 2005/06/07 (regression 4) (Table A4), or, as we show in Table A5, if we measure the effects of cloud for the years 2007 and 2015 (regression 1), 2017 (regression 2) or 2019 (regression 3). Across these regressions the estimated effect of the AIA on cloud adoption was between -11 and -17 percentage points.

5.2 Types of cloud and capital investment and the measurement of the AIA

The detailed nature of the UK data allows us to further explore how the AIA policy is linked to different types of investment and different types of cloud services. Within Table 4 Panel A, we begin by separating the aggregate investment (shown in the previous Table 3) into hardware (column 1), software (column 2), plant and machinery (column 3), vehicles (column 4), and land and building investment (column 5). Similarly, in Panel B we study the effect of the AIA on the different types of cloud included in the E-Commerce survey. These are cloud databases (column 6), storage (column 7), customer relations management (CRM) software (column 8), office software (column 9) and email (column 10).[34]

We find that the AIA incentivized firms to invest only in the types of capital that were

upon request.

[34] We report results for finance software and own software in Table A6, along with Eurostat (2018) definitions of low, medium and high-tech types of cloud technologies.

eligible for the allowance, consistent with evidence on capital incentive policies in other contexts (Cummins et al., 1994; House and Shapiro, 2008; Zwick and Mahon, 2017; Ohrn, 2018; Maffini et al., 2019). For example, the impact of the policy on treated firms leads to an increase in plant & machinery, vehicles, hardware and software investments (see Table 4).The treated firms increase investment in hardware by 41.3% and software by 27.8%. Importantly, we find that the AIA was not linked with increased investments in land and buildings by UK firms, a type of investment that was not eligible for the AIA. [35]

The AIA capital incentive strongly predicts reduced rates of adopting cloud services related to the storage and processing of data, but not all types of cloud. The effect of the policy is particularly pronounced for cloud hosting of databases, storage of files and CRM software. Firms treated by the AIA are around 9.4% less likely to adopt cloud database services and 9.7% less likely to adopt cloud storage compared to the control group. Of interest we find no effect on the probability to adopt cloud for access to office software and email services. These are the least technologically sophisticated forms of cloud services for which there is information and the least likely to be viewed as a substitute for traditional IT capital investments. We find similar zero effects for finance software and hosting the firm's own software in Table A6 in the Appendix.

The fact that the AIA incentive does not affect ineligible capital investment (i.e. land and buildings), nor all cloud types (such as for accessing email), provides some reassurance that we are not capturing unobservable firm specific productivity or demand shocks that are increasing investment and technology adoption throughout the firm. Rather, the effects of the AIA are specific to the types of investment and technology adoption that would be expected to change as a consequence of the AIA policy and to the way that we classify firms as being treated by the AIA.

[35] Since the investment outcomes are in logs, the percentage increase in hardware investment is calculated as 41.3% = exp(0.346)-1. Software investment increases are calculated similarly.

Table 4: Effects of AIA on investment and cloud types

	Panel A: Investment				
Regressions	(1)	(2)	(3)	(4)	(5)
Dependent variables	Hardware Investment	Software Investment	Plant & Mach. Investment	Vehicles Investment	Land & building Investment
AIA Dummy	0.346***	0.246***	0.549***	0.214***	-0.012
	(0.079)	(0.070)	(0.100)	(0.072)	(0.086)
Observations	17,651	24,313	22,569	18,583	22,327
	Panel B: Cloud Adoption				
Regressions	(6)	(7)	(8)	(9)	(10)
Dependent variables	Cloud Databases	Cloud Storage	Cloud CRM	Cloud Office	Cloud Email
AIA Dummy	-0.094***	-0.097***	-0.091***	0.001	-0.045
	(0.040)	(0.035)	(0.037)	(0.027)	(0.032)
Observations	2,200	2,200	2,200	2,200	2,200

Note: Time Period: Investment regressions use annual data for the years 2007 to 2013. Cloud regressions use data for 2007 and 2013. Panel A displays separate regressions for the different types of capital investment while Panel B presents estimations for each type of could services. Capital investment variables are in (logged) thousands of pounds, while the cloud variables are a dummy variable. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. Regressions use a binary AIA eligibility indicator. The regressions in Panel A are estimated using the method outlined in Callaway and Sant'Anna (2021) and those in Panel B use difference-in-differences. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age. These are not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

5.3 Big data and AI

Having established the robustness of the effects of the AIA on cloud, we next explore whether the policy affected other types of technology adoption, namely big data and AI. The effect of capital incentives on these technologies depends on the extent to which firms can use their own IT capital for big data analytics and AI, or rather, whether cloud computing is preferred. If capital incentives increase the IT hardware to store and process data within the firm, then this may encourage their adoption. However, cloud services are often cited as being intertwined with big data and AI, because the volumes of data involved require large amounts of storage and processing power. Cloud offers storage and processing capabilities in ways that are more flexible and cost effective than installing the physical server infrastructure (Brown et al., 2011).[36] This opens the possibility that capital investment policies may instead act to slow the diffusion of big data analytics and AI across firms.

The evidence we find points to capital incentives discouraging the use of big data analytics and AI. According to our estimates, changes to the marginal tax rate that followed from changes to the AIA thresholds reduced the use of big data analytics by around 18 percentage points (using either a long difference between 2007 and 2015 or 2007 and 2019, see columns 1 and 2 in Table 5). Similarly, we find that firms which qualify for the AIA exhibit a lower propensity to adopt AI. We find that treated firms were around 3 percentage points less likely to AI (see Table 5 column 3).

To give an indication of the magnitude of the aggregate slowdown in the use of these new digital technologies, we repeat our estimation applying sampling weights. The weighted regressions show similar coefficients to our baseline in Table 5, which we combine with 46% of UK firms being treated by the AIA policy by 2019, to roughly calculate the aggregate slowdown in technology diffusion.[37] Our results imply an aggregate reduction in big data

[36] As is often quoted in the IT systems literature (e.g. Armbrust et al. (2009)), 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.

[37] Further details are discussed under similar estimation for cloud usage on page 19. All statistics mentioned in this paragraph are weighted means (applying sampling weights).

Table 5: The effects of AIA on the adoption of big data and AI

Regressions	(1)	(2)	(3)
Variables	Big Data 2007/15	Big data 2007/19	AI 2007/19
AIA Dummy	-0.185***	-0.182***	-0.027***
	(0.030)	(0.034)	(0.011)
Observations	2,262	1,746	1,746

Note: Regression 1 uses data for 2007 and 2015; regression 2 and 3 use data for 2007 and 2019. The dependent variables big data and AI adoption are dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility and are estimated via difference-in-differences. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

analytics use of 7 percentage points and AI use by 1 percentage point. While seemingly small numbers, these should be considered in the context that only 3% of UK firms used AI by 2019 [38]. Moreover, big data analytics use would have been 14% higher and AI 30% higher in 2019 in the absence of the AIA policy. Or put another way, the policy slowed down big data analytics by 1.4 years and AI diffusion by 1.2 years.[39] This delay is large, especially for AI, which has only emerged in the US in 2015 (Bloom et al., 2022).

5.4 Data workers

The previous sections found that the AIA policy discouraged firm adoption of data analytics technologies, such as cloud, big data analytics or AI. In this section we examine whether this also materialises in the demand for workers performing data analytics tasks.

We find evidence that the firms treated by the AIA capital incentive reduced their demand for data analytics workers, but that this had no effect on the other types of workers. The wages of workers that perform data analytics fell by 1.5% to 1.6% in firms treated by the

[38] AI use is 3.4% in 2019, and assumed to be zero in 2007, corresponding to the 1.7% in Table 2

[39] In our data, big data analytics and AI diffusion were increasing approximately 5 percentage points and 1 percentage points per year, respectively.

Table 6: The effects of AIA on the demand for data workers

Regressions	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Worker Wages					
Occupation Group	Non-Data		Other Data		Data Analytics	
Year	2007-2013	2007-2019	2007-2013	2007-2019	2007-2013	2007-2019
AIA Dummy	-0.006	-0.008	0.008	-0.011	-0.015*	-0.016**
	(0.005)	(0.006)	(0.012)	(0.009)	(0.009)	(0.007)
Observations	144,136	288,347	30,812	61,863	51,415	104,859

Note: Worker-level regressions using annual data. Worker wages are in (logged) thousands of pounds. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. Regressions use a binary AIA eligibility indicator. Data occupation groups are defined following Corrado et al. (2022). Specifically, Data Analytics reflects occupations with time used for data intelligence. The remaining occupations are decomposed into Other Data, those with time used for creating data stores, databases or software; and Non-Data, those that do not spend time on data activities. The regressions are estimated using the method outlined in Callaway and Sant'Anna (2021). All regressions include year and worker fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age and worker controls for age, tenure, tenure squared, skilled occupation dummy, gender and the interactions of the other worker controls with gender. These are not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

AIA, compared to these same workers in non-treated firms (columns 5 and 6). In contrast, the wages of workers that perform other data tasks, related to creating databases, data stores or software (columns 3 and 4), and workers that do not perform data tasks (columns 1 and 2), were not significantly affected. Thus, the AIA policy does not seem to affect the demand for workers upstream in the data value chain, who create and store data, but rather it is the downstream processing and analysis of data that is constrained. Moreover, it appears the AIA policy did not affect labor demand in general for treated firms, but specifically reduced demand for the subset of workers performing data analytics tasks.

5.5 Robustness

In this section we conduct a series of robustness tests of the baseline results. We first explore a continuous treatment measure that takes into account the size of the investment incentive available to each firm. In Table 7 we replace the dummy treatment variable with a continuous version that measures the number of pounds a firm's average 2005/06 investment is below the AIA threshold in that year. By so doing we attempt to capture differences in how strongly a firm was treated by the AIA - firms with a larger unused investment allowance are likely to have a stronger incentive to invest more.[40] As the estimation method of Callaway and Sant'Anna (2021) is applicable only for binary treatment variables, in the investment regression we take advantage of the recent development by Gardner (2022) that allows for continuous treatment in two-way fixed effects settings with a staggered treatment design.[41] For the cloud regression we continue to use a long-difference specification estimated using OLS. These results provide further evidence that firms with the greatest scope for increasing investment responded to the AIA by increasing their investment and reducing the likelihood of adopting cloud services. Each additional £1,000 of AIA allowance reduced cloud diffusion by 0.3 percentage points.[42]

Given the focus of the paper, we concentrate the remaining tests of robustness on the adoption of cloud. Investment data in the UK is, as in most other countries, highly skewed. A small number of firms make very large investments, whereas most firms invest a more modest amount each year. The concern is therefore whether our results are driven by the presence of these largest firms. In column 1 of Table 8 we exclude firms with the largest 5 percent of investment, using investment defined consistent with the treatment status of the firm i.e. the average across 2005/06, while in column 2 we exclude the largest 10 percent

[40] We also examined AIA allowance quartiles and found evidence that the impact of the AIA allowance is largely increasing linearly by quartile. Thus, the continuous measure employed in Table 7 appears appropriate. Results are available upon request.

[41] This uses the estimation command that implements the approach of Gardner (2022) created by Butts and Gardner (2021).

[42] Each additional £1,000 of AIA allowance also increases investment by 0.4%.

Table 7: Effects of AIA on total investment and cloud: robustness to continuous measure

Regressions	(1)	(2)
Dependent variable	Total investment	Cloud
AIA available allowance	4.260***	-2.663***
(continuous measure)	(1.043)	(0.678)
Observations	23,711	2,200

Note: Time Period: Investment regressions use annual data for the years 2007 to 2013. Cloud regressions use data for 2007 and 2013. The AIA allowance is calculated taking the average investment values for firms in 2005/06 and calculating how far this lagged investment average is above or below the AIA threshold in any given year. This is expressed in millions of pounds. All regressions are estimated using the approach of Gardner (2022). All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

of investment. This removes around 110 observations from column 1 and a little under 220 from column 2. We also test whether the results for cloud adoption are driven by the use of firms that make very little investment in capital, including IT capital. In columns 3 and 4 we also exclude the smallest 5 and 10 percent of firms. The results for cloud adoption are robust to this sample restriction, with the effect of the AIA being negative throughout. Importantly the coefficient estimate remains broadly stable across these regressions.

In a second robustness test, we exclude firms that were eligible for other policies during our sample period which may have influenced investment and cloud adoption behaviors. Until 2008 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, as considered by Maffini et al. (2019). In order to examine the robustness of the effects of AIA on firm investment decisions, 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. Despite this, our results are robust to the exclusion of these firms (see column 5 in Table 8). The signs and statistical significance of the use of cloud services are consistent with the baseline results.

We also consider the potential that our results capture a change in the definition of SMEs by the EU in 2008 which in turn affected qualification for the R&D Tax Relief Scheme for UK firms. This definition change shifted the qualifying threshold of assets from €43 million to €86 million, the employment threshold from 249 to 499, and the sales threshold from €50 million to €100 million (Dechezleprêtre et al., 2016). We start by converting these thresholds to sterling equivalents using the average sterling-euro exchange rate in 2008 of 0.80 and then exclude firms that would have been affected by this change in the year the change occurred. Specifically, we exclude firms that become eligible for the R&D incentive because of the change in the scheme design. The results for these regressions again imply that this does not explain our main findings (see column 6 in Table 8). We continue to find that capital investment policies reduce the adoption of cloud services by treated firms.

Next, we consider the robustness of our baseline results to the inclusion of additional control variables. The adoption of emerging technologies, including cloud, is typically positively correlated with firm size and industry characteristics. To control for possible underlying trends in the adoption of cloud that differ according to the size of the firm in regression 7, we allow for differences in the trend rate of cloud adoption between firms of different employment sizes. For these regressions we separate firms into different employment size bands (1-49, 50-99, 100-249, 250-499, 500-999, 1000+) and then interact these with year dummies. In regression 8 we control for differences in the trend rate of adoption for firms in different (2-digit SIC) industries. The estimated effect of the AIA policy is somewhat smaller in these two regressions at 9 and 12 per cent, respectively, but the estimated coefficient remains statistically significantly different from zero.[43]

[43]Our results are also robust to the exclusion of the few firms that changed their accounting year end during our sample period, see Table A7 in the Appendix.

Table 8: The effects of AIA and cloud adoption: sample restrictions and additional controls

Regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Cloud computing							
Restrict/controls	<95th percentile investment	<90th percentile investment	>10th percentile investment	>5th percentile investment	Exclude 1st-year allowance	Exclude R&D tax credit firms	Employment band-year	Industry 2-digit - year
AIA Dummy	-0.149***	-0.136***	-0.149***	-0.118***	-0.104**	-0.186***	-0.090**	-0.123***
	(0.040)	(0.040)	(0.058)	(0.046)	(0.048)	(0.040)	(0.043)	(0.045)
Observations	2,090	1,980	1,980	2,090	1,962	2,094	2,202	2,190

Note: Time period: Cloud regressions use data for 2007 and 2013. The dependent variable cloud adoption is a dummy variable. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility indicator and are estimated via difference-in-differences. Regression 1 excludes largest firms in the top 5% of the investment distribution, while regression 2 excludes those in the top 10%. Regressions 3 and 4 exclude the smallest firms in the bottom 5% and 10% of the investment distribution respectively. Regression 5 restricts firms from the sample which qualified for the first-year allowance while regression 6 excludes those firms which fell under the new EU SME classification in 2008. Regression 7 includes employment size band-year controls while column 8 includes 2-digit industry-year fixed effects. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.6 AIA and heterogeneity

The literature studying the effects of cloud on firm performance strongly suggests the effects of this technology are heterogeneous (Bloom and Pierri, 2018; Jin and McElheran, 2017; DeStefano et al., 2023). In this section we explore whether the effects of this particular capital incentive policy differ according to the size or the industry of the firm.

The shift in the nature of IT costs from a fixed to a largely variable cost because of the cloud, has enabled new business models, allowing entrants to scale operations quickly without the need for acquiring a mass of IT assets or labor (DeStefano et al., 2023). This has typically been labeled '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, limited collateral and demand uncertainty. 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, for example, Cummins et al. (1994); Hassett and Hubbard (2002); Gorodnichenko and Schnitzer (2013).[44]

In Table 9 we assess the extent to which firm size leads to differentiating effects in adoption as a result of the AIA policy. To do so we interact the AIA variable with a binary variable indicating firms with less than 50 employees in 2007. In the Appendix Table A9 and Table A10 we also use thresholds of 100 and 150 employees respectively. The results in Table 9 find a stronger effect of the AIA on SMEs compared to large firms.[45] The AIA policy caused both SMEs and large firms to become significantly less likely to adopt cloud, big data and AI. However, in all cases the estimated effect on SMEs are more pronounced. In column 1, the coefficient suggests that smaller firms (with less than 50 employees) were 37 percentage points less likely to adopt cloud technologies, compared to 14 percentage points for larger

[44]The data we use do not allow us to capture financial constraints at the firm level. We instead explored the use of industry-level measures of financial constraints. We find no evidence of heterogeneity associated with industry-level measures of financial constraints, see Table A8.

[45]We also explored heterogeneity associated with the age of the firm. As shown in Table A11, the effects of the AIA do not appear to differ between younger and older firms, irrespective of the way that they are defined.

firms. The AIA policy therefore slows down cloud diffusion the most amongst firms which benefit the most from its invention.[46]

Table 9: Heterogeneous effects of AIA and Cloud, Big data and AI adoption, by firm size

Regressions	(1)	(2)	(3)
Dependent Variable	Cloud	Big Data	AI
AIA Dummy	-0.141***	-0.171**	-0.026**
	(0.042)	(0.034)	(0.010)
AIA Dummy*Emp<50	-0.228**	-0.184*	-0.019**
	(0.103)	(0.095)	(0.007)
Observations	2,220	1,746	1,746

Note: Regression 1 use data for 2007 and 2013, regressions 2 and 3 use data for 2007 and 2019. The employment interaction is =1 if the firm had fewer than 50 employees in 2007. The dependent variables cloud, big data and AI are a dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility and are estimated via difference-in-differences. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

We also explore heterogeneity in the effects of AIA policy by firms in knowledge intensive industries. The literature has shown, for example, that firms who possess considerable amounts of intangibles including data, intellectual property or high skilled employees disproportionately adopt digital technologies (Autor et al., 2003; Bloom et al., 2012; Haskel and Westlake, 2018; Eckert et al., 2020; DeStefano et al., 2022). We explore this question by including an industry interaction term identifying firms in knowledge intensive sectors (Eurostat, 2014).[47]

The results in Table A14 are mixed, with some evidence that firms in less knowledge intensive sectors are more affected by the AIA policy. In column 1, we find that the negative effect of the AIA policy on cloud is only present in less knowledge intensive sectors, for

[46] See for instance Jin and McElheran (2017); DeStefano et al. (2023).

[47] In Table A12 we consider the robustness to a measure of skill intensive sectors (Eckert et al., 2020) and in Table A13 we use an industry-level measure of R&D intensity.

knowledge intensive sectors the coefficients are close to zero (-0.23 + 0.22). Whereas for big data analytics and AI we don not find evidence of heterogeneity by knowledge intensity.

6 Conclusion

The arrival of cloud computing is changing the way firms access IT; however, little is known about whether the policies designed for earlier forms of technology can be extrapolated. This paper examines whether capital incentives distort firm decisions to adopt cloud or invest in physical IT, and also how this impacts the diffusion of big data analytics and AI. To do so, we take advantage of the introduction and subsequent changes to a UK tax incentive for tangible capital investment – the Annual Investment Allowance (AIA).

We find that firms eligible for the AIA increase their capital investment, including IT and hardware capital, 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 (partial) substitutes – a reduction in the price of IT investment leads to a substitution away from cloud and towards traditional IT. Earlier research suggests smaller firms benefit most from the cloud (through the flexible variable costs it provides); however, we find that these are precisely the firms for which diffusion is most constrained by the capital incentive. Furthermore, the AIA also reduced demand for data analytics workers and induced a lower likelihood of using big data analytics and AI, confirming that cloud computing is a key complement for the use of big data and AI. Our estimates suggest that the policy slowed the aggregate diffusion of cloud, big data analytics and AI by more than one year.

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 adopters of cloud compared to other high-income economies, in part due to the early roll-out of superfast fiber broadband (DeStefano et al., 2023); therefore, these findings offer a possible prognosis for other economies. By incentivizing 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 can lead to knock-on effects by further slowing the diffusion of other data-driven technologies that leverage the cloud, such as big data analytics and AI. If, as Goldfarb et al. (2023) suggest, and AI/big data are general-purpose technologies, this may lead to a longer term effect on growth. General purpose technologies are characterized by virtuous circles of innovation between those sectors creating and those using the technology (Bresnahan and Trajtenberg, 1995).

Capital incentive policies are often justified based on the market failures of economies of scale and credit market imperfections especially for smaller firms. However, by shifting IT costs from a largely sunk cost to a variable cost, cloud itself can alleviate some of these market failures. More specifically, cloud computing shifts the economies of scale in IT from the user firm to the cloud provider - who install giant data centers comprised of hundreds of thousands of servers, but pass on a variable cost to cloud users. Our results suggest that policies designed for firms comprised of PCs, servers, bricks and mortar may need reconsideration for business models that are increasingly comprise of data and other intangibles.

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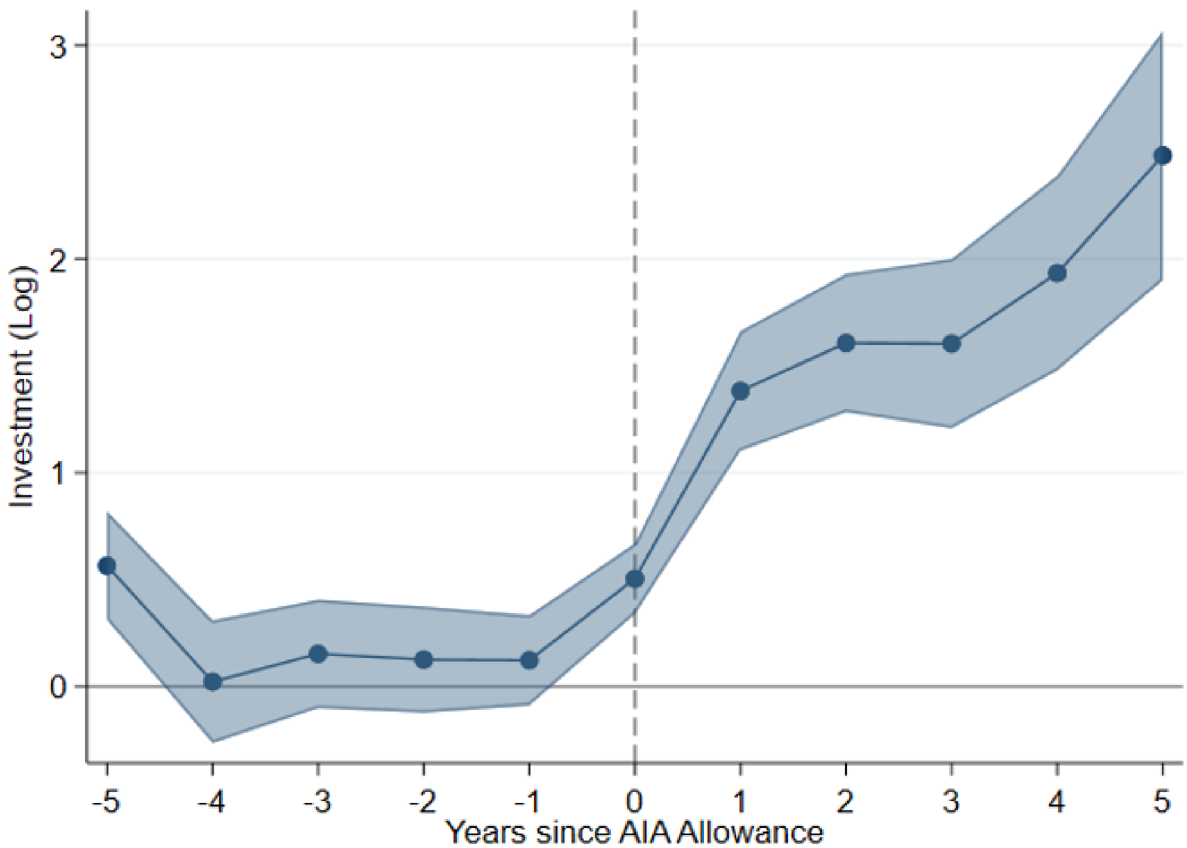
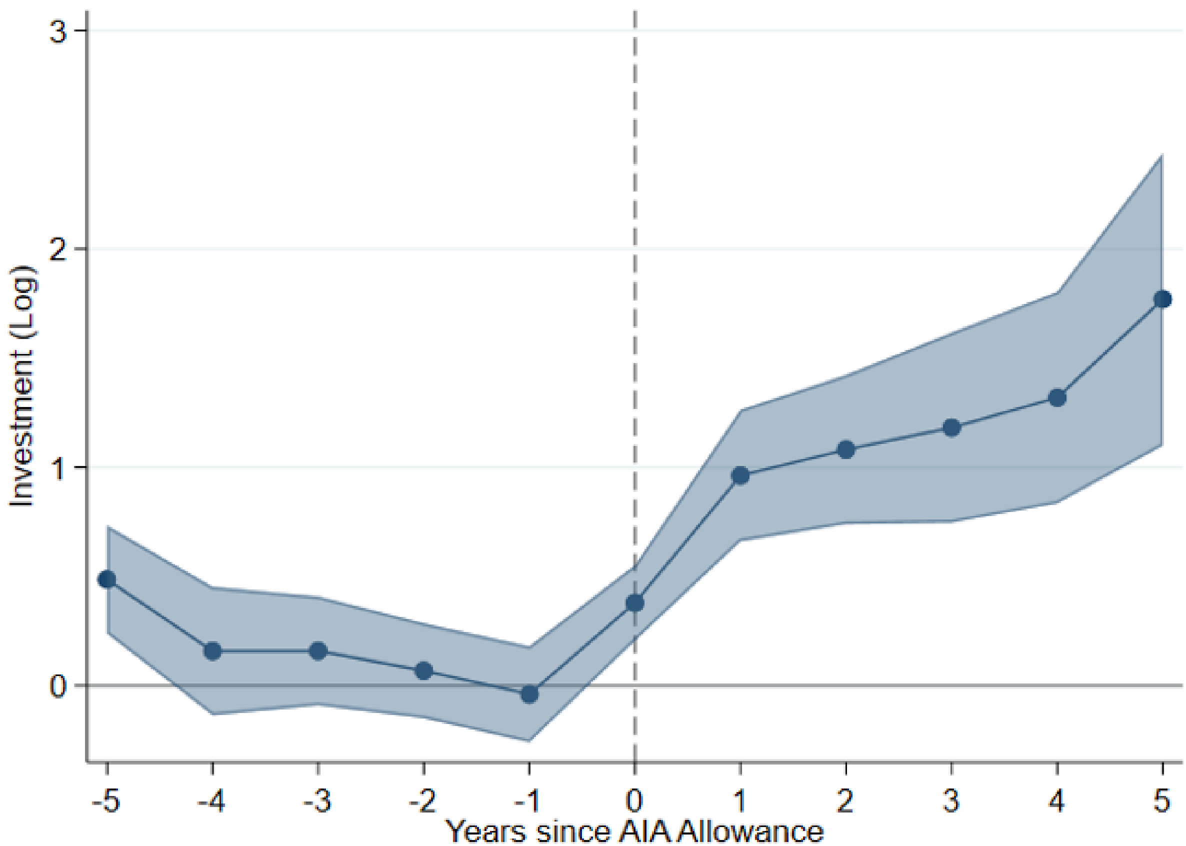
Appendix A

Figure A1: Total investment, CSDID, 2-year average 06/07



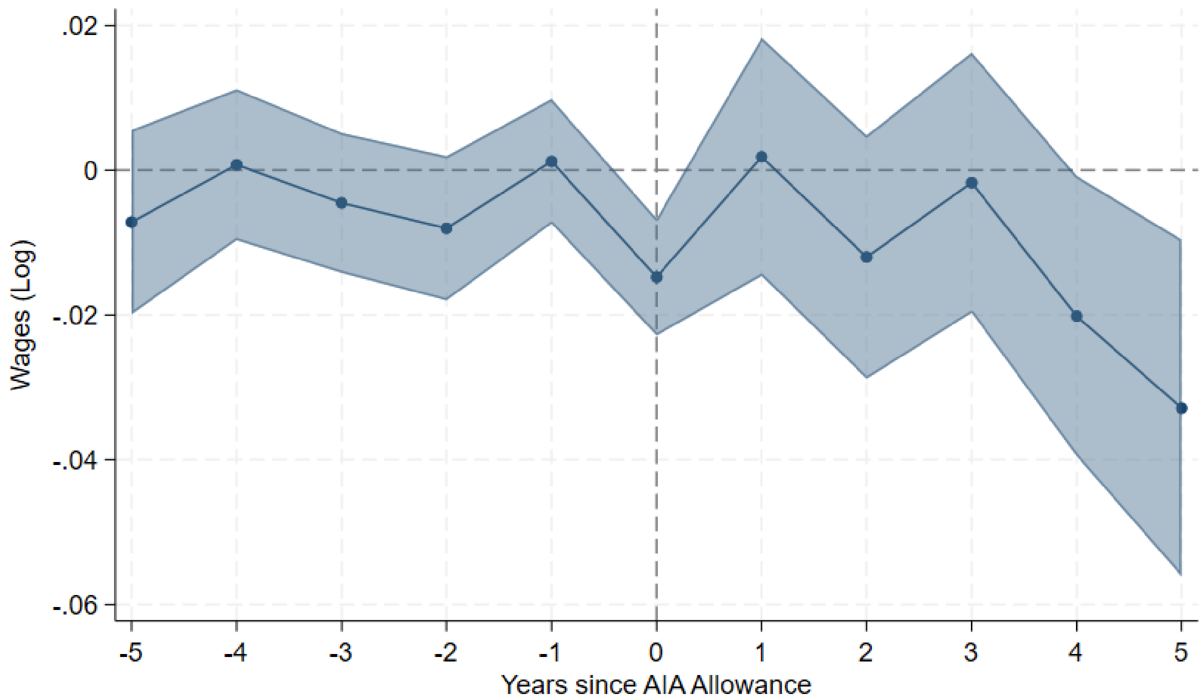
Notes: Data period: 2007-2013.The above figure presents the coefficients and 95 per cent confidence intervals of event study regressions – reflecting firm total investment in the periods before and after changes in the AIA threshold. The threshold is calculated using 2-year average investment in years 2006/2007. Event time is equal to 0, the preceding year is event time of –1, the year after the event is +1, and so on. The estimation follows the method of Callaway and Sant'Anna (2021), see equation 1.

Figure A2: Total investment, CSDID, 3-year average 05/06/07



Notes: Data period: 2007-2013. The above figure presents the coefficients and 95 per cent confidence intervals of event study regressions – reflecting firm total investment in the periods before and after changes in the AIA threshold. The threshold is calculated using 3-year average investment in years 2005/2006/2007. Event time is equal to 0, the preceding year is event time of −1, the year after the event is +1, and so on. The estimation follows the method of Callaway and Sant'Anna (2021), see equation 1.

Figure A3: Wages of data analytics workers, CSDID



Notes: Data period: 2007-2019. The above figure presents the coefficients and 95 per cent confidence intervals of event study regressions – reflecting worker wages in the periods before and after changes in the AIA threshold. The threshold is calculated using 2-year average investment in years 2005/2006. Event time is equal to 0, the preceding year is event time of −1, the year after the event is +1, and so on. The estimation follows the method of Callaway and Sant'Anna (2021), see equation 2.

Table A1: Firm descriptive statistics for all time periods

Variables	Mean	SD	Observations	Sample coverage
		Annual Investment Allowance		
AIA dummy	0.203	0.403	41,996	(2007-2019)
AIA dummy	0.087	0.282	2,264	(2007 2013)
AIA dummy	0.15	0.358	2,264	(2007 2015)
AIA dummy	0.149	0.356	2,276	(2007 2017)
AIA dummy	0.215	0.411	1,748	(2007 2019)
		Firm investments (logs)		
Total investment	6.595	2.426	42,011	(2007-2019)
Software investment	2.378	2.633	42,011	(2007-2019)
Hardware investment	3.781	2.086	20,599	(2007-2019)
Plant-Machine investment	5.943	2.433	34,442	(2007-2019)
Vehicles investment	3.683	2.22	29,335	(2007-2019)
Land-Building investment	1.161	2.461	38,937	(2007-2019)
		Firm technology adoption		
Cloud	0.327	0.469	2,264	(2007 2015)
Cloud	0.361	0.48	2,276	(2007 2017)
Cloud	0.832	0.486	1,748	(2007 2019)
Cloud	0.439	0.496	5,084	(2007,13,15,17,19)
Cloud Storage	0.314	0.464	5,084	(2007,13,15,17,19)
Cloud Data	0.221	0.415	5,084	(2007,13,15,17,19)
Cloud CRM	0.169	0.375	5,084	(2007,13,15,17,19)
Cloud Finance Software	0.135	0.341	5,084	(2007,13,15,17,19)
Cloud Office Software	0.293	0.455	5,084	(2007,13,15,17,19)
Cloud Email	0.31	0.462	4,681	(2007,13,15,17)
Cloud Own Software	0.15	0.357	5,084	(2007,13,15,17,19)
		Control variables		
Multi-establishment	0.736	0.441	42,011	(2007-2019)
Number of establishments	49.528	263.708	36,196	(2007-2019)
Foreign owned	0.348	0.476	42,011	(2007-2019)
Age (log)	3.418	0.371	42,011	(2007-2019)

Note: All investment variables are in log thousands of UK pounds, deflated to 2007 prices using 4-digit PPI deflators provided by the ONS.

Table A2: Worker descriptive statistics

Variables	Mean	SD
Wages and Occupation Classification		
Wages (logs)	6.193	0.538
Data Analytics	0.230	0.421
Other Data	0.136	0.342
Non-Data	0.634	0.482
Control variables		
Age (logs)	3.662	0.308
Male	0.702	0.457
Tenure (logs)	1.834	0.988
Tenure Squared	155.365	296.514
Skill	2.516	1.022

Note: Reflect annual data 1997 to 2019, and all variables have 455,069 observations. Wages are in log thousands of UK pounds, deflated to 2007 prices using 4-digit PPI deflators provided by the ONS. Skill is a categorical variable taking the values 1 to 4, using the ONS definition of skilled occupations. Regressions also include interactions of these worker control variables, which are not reported here for parsimony. Data occupation dummies are defined following Corrado et al. (2022). Specifically, Data Analytics reflects occupations with time used for data intelligence. The remaining occupations are decomposed into Other Data, those with time used for creating data stores, databases or software; and Non-Data, those that do not spend time on data activities.

Table A3: The effects of AIA on total investment, robustness to different time periods

Regressions	(1)	(2)	(3)	(4)
Description	2007-15	2007-17	2007-19	Long difference 2007-13
AIA Dummy	0.457***	0.545***	0.525***	0.341***
	(0.104)	(0.103)	(0.103)	(0.126)
Observations	26,504	31,765	36,554	4,678

Note: Time period: Regression 1 uses data from 2007 to 2015, regression 2 from 2007 to 2017, regression 3 from 2007 to 2019, and regression 4 for 2007 and 2013. Total investment is in (log) thousands of pounds. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. Regressions use a binary AIA eligibility indicator. Regressions 1 to 3 are estimated using the method outlined in Callaway and Sant'Anna (2021) and regression 4 uses OLS. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age. These are not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A4: The effects of AIA on total investment and cloud, robustness to different historic investment values

Regressions	(1)	(2)	(3)	(4)
Dependent variable	Total Investment	Cloud	Total Investment	Cloud
	2-year average 2006/07		3-year average 2005/06/07	
AIA Dummy	1.271***	-0.148***	0.879***	-0.170***
	(0.114)	(0.039)	(0.118)	(0.041)
Observations	21,762	2,198	21,782	2,198

Note: Time period: Total investment regressions use annual data for the years 2007 to 2013. Cloud regressions use data for 2007 and 2013. Total investment is in (log) thousands of pounds, while cloud is a dummy variable. Regressions 1 and 2 identify treated firms by taking the average investment values for firms in 2006/07 while regressions 3 and 4 use average investment values for 2005/06/07. Regressions use a binary AIA eligibility indicator. Regressions 1 and 3 are estimated using the method outlined in Callaway and Sant'Anna (2021) and regressions 2 and 4 use OLS. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age. These are not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A5: The effects of AIA on Cloud Adoption in 2015, 2017 and 2019

Regressions	(1)	(2)	(3)
Cloud data	2007-15	2007-17	2007-19
AIA Dummy	-0.173***	-0.119***	-0.164***
	(0.032)	(0.031)	(0.030)
Observations	2,262	2,274	1,746

Note: Time period: Regression 1 uses data for 2007 and 2015; regression 2 uses data for 2007 and 2017 and regression 3 uses data for 2007 and 2019. Cloud is a dummy variable. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. Regressions use a binary AIA eligibility indicator. All regressions uses OLS and include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age. These are not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A6: Effects of AIA on cloud adoption types

Regressions	(1)	(3)	(4)	(5)	(6)
Dependent variables	Cloud Finance	Own Software Cloud	Cloud Low tech	Cloud Med tech	Cloud High tech
AIA Dummy	-0.016	-0.026	-0.018	-0.094***	-0.086**
	(0.024)	(0.027)	(0.026)	(0.032)	(0.034)
Observations	2,200	2,200	2,200	2,200	2,200

Note: All regressions use data for 2007 and 2013. Cloud variables are binary. Cloud low, medium and high tech are defined following (Eurostat, 2018). According to this definition, basic cloud technologies include email, office software, or file storage via cloud. Medium tech cloud use means employing at least one of the basic cloud services along with cloud for hosting the enterprise's database(s). High tech cloud use means employing of at least one of the basic cloud services as well as at least one of the more advanced cloud services including, hosting the enterprise's database(s), Finance Software, CRM and processing services. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions are estimated using OLS and include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A7: Excluding Observations that change accounting year end during the sample window

Regressions	(1)	(2)
Dependent variable	Total investment	Cloud
AIA Dummy	0.529***	-0.186***
	(0.144)	(0.047)
Observations	13,399	1,492

Note: Time period: Total investment regressions use annual data for the years 2007 to 2013. Cloud regressions use data for 2007 and 2013. Total investment is in (log) thousands of pounds, while cloud is a dummy variable. Regressions exclude firms which change their accounting year end during the sample period. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. Regressions use a binary AIA eligibility indicator. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age. These are not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A8: The effects of AIA on Cloud, heterogeneity with financial dependence

Regressions	(1)	(2)	(3)
Dependent variable		Cloud	
Variables	Leverage Ratio	Cash Holdings	Interest Expenses
AIA Dummy	-0.197	-0.211**	0.338
	(0.163)	(0.096)	(0.321)
AIA Dummy*Fin. Dep.	0.160	1.145	-8.602
	(0.619)	(1.776)	(5.550)
Observations	2,164	2,164	2,164

Note: All regressions use data for 2007 and 2013. The Fin.Dep refers to the measure variable in the column heading (e.g. leverage ratio, cash holdings, interest expenses). These indicator variables are calculated as the median value across firms at the 3-digit SIC level using data from ORBIS data for the period 2000 to 2006. The dependent variable cloud adoption is a dummy variable. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility. All regressions use OLS and include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A9: Heterogeneous effects of AIA and Cloud, Big data and AI adoption, by firm size

Regressions	(1)	(2)	(3)
Dependent Variable	Cloud	Big Data	AI
AIA Dummy	-0.104***	-0.147**	-0.024*
	(0.046)	(0.036)	(0.012)
AIA Dummy*Emp<100	-0.235***	-0.201***	-0.023***
	(0.075)	(0.060)	(0.007)
Observations	2,220	1,746	1,746

Note: Regression 1 use data for 2007 and 2013, regressions 2 and 3 use data for 2007 and 2019. The employment interaction is =1 if the firm had fewer than 100 employees in 2007. The dependent variables cloud, big data and AI are a dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A10: Heterogeneous effects of AIA and Cloud, Big data and AI adoption, by firm size

Regressions	(1)	(2)	(3)
Dependent Variable	Cloud	Big Data	AI
AIA Dummy	-0.092*	-0.146***	-0.025*
	(0.049)	(0.037)	(0.012)
AIA Dummy*Emp<150	-0.200***	-0.134**	-0.009
	(0.071)	(0.055)	(0.013)
Observations	2,220	1,746	1,746

Note: Regression 1 use data for 2007 and 2013, regressions 2 and 3 use data for 2007 and 2019. The employment interaction is =1 if the firm had fewer than 150 employees in 2007. The dependent variables cloud, big data and AI are a dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A11: The effects of AIA on Cloud, heterogeneity with age

Regressions	(1)	(2)	(3)
Dependent variable		Cloud	
Variables	Age 5	Age 10	Age 15
AIA Dummy	-0.166***	-0.166***	-0.158***
	(0.040)	(0.042)	(0.045)
AIA Dummy*Age	0.070	0.004	-0.032
	(0.273)	(0.120)	(0.087)
Observations	2,200	2,200	2,200

Note: Regression 1 use data for 2007 and 2013, regressions 2 and 3 use data for 2007 and 2019. The age interaction is =1 if the firm was aged <=5, <=10 or <=15 in 2007 in regressions 1, 2 and 3 respectively. The dependent variables cloud, big data and AI are a dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A12: Heterogeneous effects of AIA and Cloud adoption, by skill intensive sectors

Regressions	(1)	(2)	(3)
Dependent variables	Cloud	Big Data	AI
AIA Dummy	-0.210***	-0.196***	-0.027**
	(0.043)	(0.035)	(0.013)
AIADummy*STS	0.217**	0.095	-0.003
	(0.087)	(0.073)	(0.015)
Observations	2,200	1,746	1,746

Note: Regression 1 use data for 2007 and 2013, regressions 2 and 3 use data for 2007 and 2019. STS sectors are classified by Eckert et al. (2020) and include Information, Finance and Insurance, Professional, Scientific and Technical Services and Management Services sectors. The dependent variables cloud, big data and AI are a dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A13: Heterogeneous effects of AIA and Cloud adoption, by R&D sectors

Regressions	(1)	(2)	(3)
Dependent variables	Cloud	Big Data	AI
AIA Dummy	-0.154***	-0.178***	-0.024*
	(0.043)	(0.036)	(0.011)
AIADummy*R&D	-0.086	-0.020	-0.021**
	(0.096)	(0.070)	(0.009)
Observations	2,200	1,746	1,746

Note: Regression 1 use data for 2007 and 2013, regressions 2 and 3 use data for 2007 and 2019. R&D intensity is constructed using R&D expenditures (weighted by employment) at the 5-digit UK SIC level.The dependent variables cloud, big data and AI are a dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A14: Heterogeneous effects of AIA and Cloud adoption, by knowledge intensive sectors

Regressions	(1)	(2)	(3)
Dependent variables	Cloud	Big Data	AI
AIA Dummy	-0.234***	-0.190***	-0.026**
	(0.046)	(0.036)	(0.013)
AIA Dummy*KIA	0.219***	0.041	-0.009
	(0.076)	(0.064)	(0.015)
Observations	2,200	1,746	1,746

Note: Regressions 1 uses data for 2007 and 2013. Regressions 2 and 3 use data for 2007 and 2019. KIA refers to knowledge intensive sectors, those where at least 33% of the workforce have a tertiary education as defined by Eurostat (2014). The dependent variables cloud, big data and AI are a dummy variables. Treated firms are identified taking the average investment values for firms in 2005/06 and calculating if this lagged investment average is above or below the AIA threshold in any given year. All regressions use a binary AIA eligibility and and are estimated via difference-in-differences. All regressions include year and firm fixed effects, as well as firm controls of lagged employment, a multi-plant dummy, foreign owned dummy and log age, not reported for brevity. Robust standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.