Intangible income shifting: the impact of digitalisation on falling corporate tax rates

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Intangible income shifting: the impact of digitalisation on falling corporate tax rates

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Abstract

Concerns over the amount of corporation tax paid by firms in digitally intensive industries have led to efforts to reform corporate tax codes at national and international levels. Despite this, there is little evidence to suggest firms in digitally intensive industries pay less corporate tax. The paper examines the interplay of digitalisation, firm size and MNE status to investigate if large, digitally intensive and multinational firms do indeed pay less tax, as measured by the cash effective tax rate (Cash ETR). It finds no significant relationship between industry digitalisation and Cash ETRs using a primary measure of industry digitalisation. However, the interactions of digitalisation, firm size and MNE status exhibit statistically significant impacts on Cash ETRs, though the magnitudes are modest. Larger firms in digital intensive industries tend to have Cash ETRs that are 1% lower than their less digital intensive equivalents. MNEs in more digital intensive industries tend to have Cash ETRs that are approximately 0.5% lower than firms in less digital intensive industries. Notably, the very largest tech firms display considerably lower Cash ETRs, thus, it would appear they provide much of the impetus for corporate tax reform.

Keywords Corporate tax · Income shifting · Digitalisation · Intangible assets · Multinational corporations

JEL Classification H25 · H26 · O33 · L10 · L20

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1 Introduction

Concerns over the amount of corporation tax paid by firms in digitally intensive industries have led to efforts to reform tax regimes at both national and international levels (Christensen et al., 2019; Lips, 2020). About half of European OECD countries "have either announced, proposed, or implemented a digital services tax" according to the Tax Foundation,[1] with digital services tax described as "one of the most fraught aspects" of international taxation (Bradford, 2023: 13).

It has been argued that digitalisation of economic activity rendered the global tax system unfit for purpose permitting large profitable corporations legally paying low tax to the jurisdictions where they operated (Young, 2024a, 2024b). Suggested reforms were the response, with the OECD pursuing a two-pillar approach to address tax challenges from digitalisation as part of the base erosion and profit shifting (BEPS) process (OECD, 2015, 2018, 2019, 2020a, 2020b). The first pillar addresses the tax base, potentially allocating more taxation rights to countries where sales occur, rather than where the selling firm is located. The second pillar addresses tax rates, focussing on the introduction of a global minimum tax for large multinational enterprises (MNEs).

Despite substantial focus on the challenges of taxing firms in an increasingly digitalised world, and a prevailing resonant *sense* of unfairness (Devereaux et al., 2021; Hakelberg, 2020), there is little evidence linking increased digitalisation and lower effective corporate tax rates. Perhaps the most common measure used is the Cash Effective Tax Rate (Cash ETR), which equals cash taxes paid divided by pre-tax income. Dyreng et al., (2008: 63) found that firms with low Cash ETRs "are well spread across industries but with some clustering", notably in oil and gas. Dyreng and Hanlon (2021) split the results by high tech and all other industries,[2] and found similar trends in both groups.

This paper examines if digitisation is linked to lower Cash ETRs after controlling for several important factors, most notably the firm's level of intangible assets and its record of prior losses. Intangible assets are referred for specific investigation, as they can make it easier for MNEs to engage in income-shifting activities, thereby lowering their Cash ETRs. Despite the importance of intangibles, they are difficult to measure accurately, as intangible costs are primarily expensed as incurred and, therefore, do not appear on the balance sheet (Barker et al., 2022; Lev, 2018). The paper takes advantage of methods to measure intangible assets at the firm level (see Peters & Taylor, 2017 and Ewens et al., 2021) applied to a dataset selected from Computstat. We also draw on Drake, Hamilton and Lusch (2020) to add a number of controls related to a firm's loss history.

The paper addresses two primary research questions:

[1] https://taxfoundation.org/digital-tax-europe-2020/ Last accessed 13.09.23.

[2] Where high tech industries are those with SIC codes 283, 357, 366, 367, 382, 384, 481, 482, 489, 737 or 873.

1. Do firms in digital intensive industries pay less tax than those in less digital intensive industries?
2. Focusing on large MNEs, how do size and MNE status interact with the degree of digitalisation?

Two distinct measures of industry digitalisation are used to address these questions. The principal measure is based on an OECD taxonomy of industry digitalisation (Calvino et al., 2018) for the years 2001–2019. The second is based on US Bureau of Economic Analysis (BEA) data which provides estimates of digitally derived gross output, value added, employment, and compensation for 92 NAICS industries. This also provides the scope to classify industries into 'digital intensive' and 'less digital intensive' categories.

The dataset assembled for the descriptive empirical analyses allow for assessment of the significance of a firm's presence in digital intensive or less digital intensive industries for its Cash ETR. The study also interacts digitalisation with firm size and MNE status to address the second question of whether the interactions of digitalisation, scale and MNE status lead to statistically significant differences in determining Cash ETRs.

We make the following contributions to the literature:

- Development and application of comprehensive firm level intangible data.
- Assessment of the impact of digitalisation at the industry level using OECD and BEA taxonomies, and
- Analysis of the interplay between size, MNE status and digitalisation on cash ETRs.

We do not proffer causal explanation in our analyses, noting rather that digitally intensive firms (or industries) may differ from others along many dimensions, including some relating to firms' cash ETRs.[3] Nonetheless, the estimates are of interest and important, particularly given the dearth of empirical support for the widely-held and asserted link between increased digitalisation and lower effective corporate tax rates.

The paper is structured as follows. Section 2 sets out the literature informing the study, while Sect. 3 outlines the research design. Section 4 provides descriptive statistics, and Sect. 5 sets out the main results. Section 6 provides robustness checks, while Sect. 7 concludes.

[3] Our estimations include a range of control variables allowing focus on the digital/tax relationship across firms of various sizes.

2 Literature review

2.1 How digital and other intangible assets can be used to lower ETRs

Income-shifting occurs when MNCs take advantage of inter-company transactions to lower ETRs. They can do so by manipulating both the terms of the transactions, and where those transactions occur (Dyreng & Hanlon, 2021; OECD, 2015). This practice can be used to recognise more income in low tax jurisdictions.

Transfer prices between MNC subsidiaries are required to be based on the 'arm's-length' principle where prices paid reflect the market price that would be paid between two unrelated firms. In practice, prices are often difficult to observe, or may be missing entirely, due to the unique nature of the transactions in question. This is often the case where part of the value is based on digital or other intangible assets that are relatively unique to the firm. Without the precedent of well-established market prices, the firm must make assumptions about the value of the assets in question, and these assumptions are likely to be influenced by tax incentives (Bilicka, 2019; Willliams, 2018).

Effects of income-shifting can be magnified by differences in tax laws across jurisdictions (Vicard, 2023; Lai, 2018). For example, some countries define residence based on incorporation, while others define it based on the location of senior management. This creates further opportunities for companies to take advantage of differences in tax codes in order to lower taxes (Dyreng & Hanlon, 2021).

Digital and other intangible assets are convenient for manipulating both the terms and locations of the transactions. Their firm-specific nature makes transactions difficult to benchmark, providing firms with scope when setting transfer prices. Furthermore, the 'location' of some intangible assets such as patents or copyrights can be easily moved between jurisdictions, depending on the incentives created by different tax codes.

2.2 Factors related to lower effective tax rates

While the taxation of the digital economy has received significant attention politically, there is little evidence to suggest that digitally intensive firms, or firms in digital intensive industries, pay less tax. Dyreng et al. (2008), Dyreng et al. (2017) and Dyreng and Hanlon (2021) use Compustat data to look at cash effective tax rates (Cash ETRs) of public firms in the U.S., where the Cash ETR is defined as the amount of cash taxes paid (as opposed to the amount appearing on the P&L) over a given period, divided by the pretax P&L income over the same period. They found that the mean Cash ETR over a one-year period was consistently lower than the 35% statutory rate (between 26.1 and 29.6% depending on the period and whether the firm was domestic or an MNE). The mean Cash ETR tended to converge to the statutory rate over longer time periods. Nevertheless, a significant number of firms were able to maintain Cash ETRs well below the statutory rate over an extended period (one quarter of firms had a ten-year Cash ETR 20% and lower in the 2008 study).

There was no estimated link to lower rates in digital intensive industries, however. Indeed, the original study found that these firms "are well spread across industries but with some clustering", notably in oil and gas (Dyreng et al., 2008: p.63). Dyreng and Hanlon (2021) split results by high tech and all other industries,[4] and found similar trends in both groups.

Dyreng and Hanlon (2021: p.389) provide an overview of the firm characteristics that are associated with lower Cash ETRs and state that "overall, the studies find that firms with more financial leverage, higher research and development expenses, and more property plant and equipment generally have relatively lower cash effective tax rates". The extent of a firm's foreign operations also impacts rates, with Rego (2003) finding that multinational firms with more extensive foreign operations have lower Generally Accepted Accounting Principles (GAAP) effective tax rates than those with less.

There is evidence connecting lower ETRs and investment in intangible assets more broadly, however. Intangible assets are non-physical, knowledge-based assets such as software, but also include other assets such as brands, patents, designs, creative works and business processes. Belz et al. (2017) carry out a meta-regression analysis to determine the relationship between R&D and effective tax rates (ETRs). They conclude that where both current and deferred taxes are included in the definition of the ETR, a 1 percent increase in R&D intensity leads to a 0.17 percent decrease in the ETR. About 0.02 percent of that figure was attributed to the impact of tax credits, with the remainder due to income-shifting activities.

Finally, the accumulation of prior year losses can have a significant bearing on *both GAAP and cash* ETRs. Henry and Sansing (2018) use a measure of tax avoidance scaled by assets rather than pretax income, which enables loss years to be included in their samples. The inclusion of these loss years removes the downward trend in their measure. Subsequently, Drake, Hamilton and Lusch (2020) found that valuation allowances (VAs), which are related to prior-period losses, are strongly related to ETRs. These VAs create a downward bias which explains almost all of the downward trend observed amongst domestic U.S. firms.

3 Research design and data

The study seeks to establish whether firms in digital intensive industries have lower cash ETRs, and how this varies with other potentially influential factors such as age, earnings history, MNE status and the level of intangible assets. Key variables used in the analysis are outlined next (all independent variables are provided in Appendix 1).

[4] Where high tech industries are those with SIC codes 283, 357, 366, 367, 382, 384, 481, 482, 489, 737 or 873.

3.1 Industry digitalisation

3.1.1 OECD measure

The primary measure of industry digitalisation is the taxonomy developed in Calvino et al. (2018) ranking industries across seven dimensions of digital maturity. Rankings were generated for two periods: 2001–2003 and 2013–2014. The results of these rankings were distilled into one overall digital intensity ranking per industry (detailed in Appendix 2). We applied the first set of rankings to data from the economic cycle of 2001–2007, and the second set to the cycle of 2008–2019.[5]

A digital dummy was created with those industries lying above the digital median assigned a value of 1. While some industries change quartile from the beginning of the period to the end, no industry goes above or below the median, hence, the digital dummy remains constant. Consistent with the terminology in this study, we refer to industries above the digital median as 'digital intensive', with those below making up the 'less digital intensive' category.

3.1.2 BEA measure

An alternative measure of digitalisation based on data from BEA was also applied. Data from BEA uses a supply/use framework to estimate gross output, value added, employment, and compensation associated with the digital economy for 2005–2019.[6] The digital economy is defined as comprising digital infrastructure (physical materials and organisational structures used to support the digital economy), e-commerce and digital services (U.S. BEA, 2021). Estimates of digitally derived gross output, value added, employment, and compensation are provided for 92 NAICS industries. BEA estimates indicate the digital economy accounted for 9.6% of US GDP in 2019, and the share within each industry varies greatly.

As for OECD data, we split industries into 'digital intensive' and 'less digital intensive' categories. There are two distinct clusters of industries, depending on whether value added, employment or compensation is used in the measurement of digitalisation. The first group tends to have 10% or less of value added/employment/compensation defined as 'digital', and fir3ms are defined as 'less digital intensive'. The second group has at least 20% and its firms are defined as 'digital intensive'. Both clusters of firms are visible from the histograms outlining each industry/year value for all three categories as provided in Appendix 3 (with the selection of the 20% cut-off value based on our visual inspection).[7]

[5] The economic cycles run from the beginning of a recession to the end of the following expansion as defined by BEA.

[6] https://www.bea.gov/data/special-topics/digital-economy Last accessed 13.09.23.

[7] While there are some industries classified as 'less digital intensive' which have measures between 10 and 20% in BEA data, there are very few firms in the Compustat data from those industries, hence their absence from the histograms in Appendix 3.

3.2 Intangible assets

Estimates of intangible capital stocks were created using a method derived from Peters and Taylor (2017) and Ewens et al. (2021). Peters and Taylor (2017) explain intangible capital as the sum of a firm's knowledge capital plus organisational capital. Knowledge capital is obtained by applying the perpetual inventory method to the firm's past research and development (R&D) expenditures. The remainder of intangible assets are classified as organisational capital, where the key assumption is that 30% of sales, general and administrative (SG&A) expenditure constitutes investment in the organisational capital stock (on assets such as human capital, brand, IT systems and organisational processes). The other 70% are assumed to support the current period's production only. This 30/70 assumption follows Hulten and Hao (2008) and Eisfeldt and Papanikolaou (2013, 2014), and is derived from Corrado et al. (2005). The latter also apply the perpetual inventory method to obtain stocks of intangible assets over time.

One element of Peters and Taylor's (2017) intangible measure distinct from earlier work is inclusion of balance sheet intangibles, primarily goodwill from externally acquired assets. They also adjust SG&A and cost of goods sold (COGS) to account for the fact that R&D expenditures are typically included within SG&A, and occasionally in COGS. These variables are henceforth referred to as adjusted SG&A (ASGA) and adjusted COGS (ACOGS).

Ewens et al. (2021) develop this method by utilising market data from stock prices and firm exits to improve key parameter estimates for the accumulation of intangible capital. A key finding of their work is that the fraction of SG&A classified as investment in organisational capital (as opposed to an immediate expense on the P&L) varies by industry, in contrast to the single 30% rate used by Peters and Taylor (2017). The fractions calculated using their preferred 'firm exit' estimation method range from 19% in the Consumer industries, to 44% and 49% in the High Tech and Health industries respectively. The other key parameter of interest is the depreciation rate of knowledge capital (accumulated R&D expenditure). Their estimates here are similar to existing BEA estimates. The parameter estimates used in this paper are based on Ewens et al. (2021), with both sets of parameters outlined in Appendix 4.

3.3 Prior period losses

Accounting for prior period losses is important when addressing questions of ETRs, as accumulated losses can provide a tax shield if and when firms return to profitability. Drake et al. (2020) account for prior period losses through their impact on valuation allowance (VA) adjustments, the recording (release) of which will increase (decrease) GAAP ETRs in a given year. This is based on a logistic model which estimates the VA release probability based on the firm's earnings history, tax loss carry-forwards and free cash flows. Using these estimates significantly improves the explanatory power of both GAAP and cash ETR models because including only firms with positive pre-tax income creates a biased sample as they are more likely to have tax shields from prior year losses.

3.4 Sample selection and data preparation

We use Compustat data in common with Dyreng et al. (2008), Dyreng et al. (2017)) and Drake et al. (2020) and follow a similar sample selection process. A key selection criterion is the removal of firms with negative pretax income. This is due to the difficultly of interpreting negative ETRs (which can occur due to negative pretax income and negative cash taxes paid). This does create selection bias issues however, as outlined by Drake et al. (2020) and we employ a number of variables (used in that study) to mitigate this bias (see Sect. 5.1). A full list of selection criteria is outlined in Appendix 5.

In addition, the 1% tails and any value of more than 3 standard deviations from the mean were removed for key regression variables, following Calligaris et al. (2018) and De Loecker et al. (2020).

3.4.1 Deflation of variables

The regression variables are a mix of ratios (such as R&D/sales) and absolute values (such as sales and the estimates of intangible capital). Where absolute values are used, the Compustat values are deflated by an appropriate deflator to make them comparable over time. Deflators for gross output, labour costs and intermediates were obtained from BEA, while deflators for fixed capital were taken from OECD STAN. All values are deflated relative to 2010 levels. Full details of processes to calculate these deflators are provided in Appendix 6.

4 Descriptive statistics

Summary statistics for all variables are provided in Appendix 7. An aspect worth highlighting is that firms from digital intensive industries (per OECD definition) are over-represented in Compustat data. Digital intensive industries make up 18/33 (56%) of the NACE A38 industries in the final sample, while 63% of firm/year observations are from these industries.

The second measure based on BEA data is narrower, with between 8 and 10 (depending on the year) of the 92 NAICS industries classified as digital intensive. The industries are considerably over-represented in Compustat, however, with the result that 33% of total firm-year observations are from 'digital intensive' industries by this measure. The correlation between the two dummies is 0.50. All industries defined as digital intensive under the narrower BEA measure are also defined as digital intensive under the OECD measure.

4.1 ETR trends

The mean Cash ETR for the period 1988–2019 was 27%. This is lower than figure of 29% reported in Dyreng et al. (2017), and is the result of a longer time span and a continued downward ETR trend. Figure 1 sets out the trend in mean ETRs over that

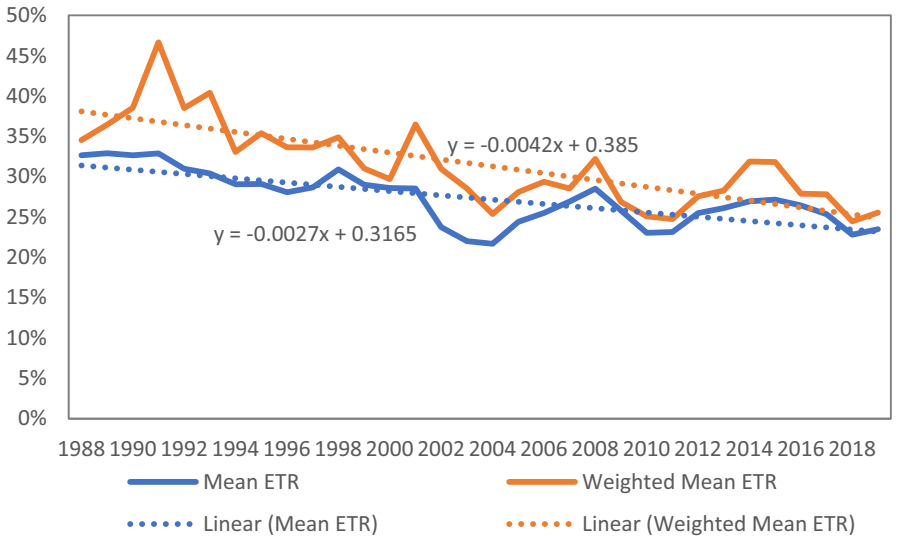


Fig. 1 Mean and weighted mean cash ETRs. *Source*: Authors' estimates—Compustat data

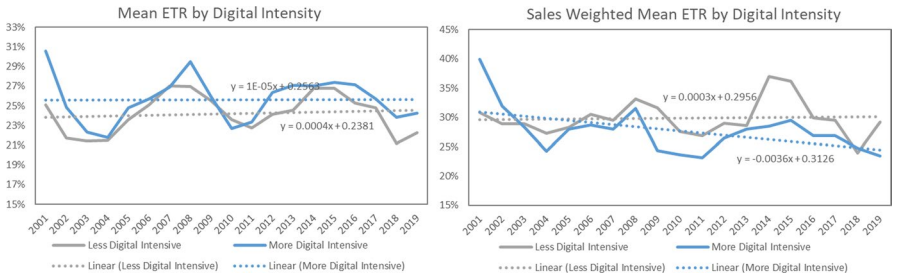


Fig. 2 Mean and weighted mean cash ETRs Split by Digital Intensity. *Source*: Authors' estimates based on Compustat data

period. A sales-weighted ETR is also included given interest in how the combination of scale, MNE status and digitalisation impacts ETRs.

The downward trend in cash ETRs identified in Dyreng et al. (2008) has continued, though the rate of decline slowed. The weighted mean ETR is higher than the mean ETR, with the gap declining over time. This means that while larger firms tend to have higher ETRs (as found in previous studies), the gap is narrowing. The decline in ETRs is, therefore, more pronounced in larger firms, as indicated by the steeper slope in the higher trendline.

Figure 2 splits the data according to categorization as digital intensive and less digital intensive. This dataset begins in 2001, as there is no measure of digital intensity before then. The unweighted ETRs have an almost flat trend post 2001. The ETRs of the more and less digital intensive industries are similar, with little or no difference in the trendlines.

Table 1 Regression of cash ETR on digital dummies and controls

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR	(4) Cash ETR
Period	'88–'19	'01–'19	'01–'07	'08–'19
Digital dummy OECD		0.002	0.009	−0.001
MNE	0.025***	0.026***	0.023***	0.029***
Trend	−0.003***	0.000	0.004***	0.000
Log sales	0.023***	0.015***	0.022***	0.010**
Log assets	−0.017***	−0.049***	−0.055***	−0.045***
R&D	−0.274***	−0.318***	−0.214***	−0.355***
PPE	−0.126***	−0.178***	−0.150***	−0.198***
Leverage	−0.021**	−0.027**	−0.012	−0.034**
Capex	−0.053***	−0.044***	−0.035**	−0.053***
Advertising	0.088	0.109	0.381***	−0.015
Special items	−1.941***	−1.520***	−1.434***	−1.556***
Lag special items	0.256***	0.035	0.185	−0.019
NOL	−0.061***	−0.041***	−0.048***	−0.033***
NOL delta	0.000	−0.000	0.007	−0.000
Five year loss		−0.015***	−0.024***	−0.008***
FCF		−0.000	−0.004	0.000
Book intangibles	0.030***			
Total intangibles		0.039***	0.036***	0.040***
Intangible share		−0.123***	−0.126***	−0.124***
Log age		0.009***	0.008	0.008**
TCJA		−0.028***		−0.027***
Extractive dummy		0.038***	0.021	0.047***
Observations	42,540	24,911	9,148	15,763
R-squared	0.094	0.078	0.092	0.075
Cluster	FIRM	FIRM	FIRM	FIRM

Robust standard errors in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

Source: Authors' estimates based on Compustat data. Variable definitions provided in Appendix 1

We see that weighted ETR from the digital intensive category is typically lower than for less digital intensive industries. In addition, we see evidence of a downward trend in the digital intensive weighted ETR of 0.36% per year that is not present in the less digital intensive category. This suggests that the interplay of scale and digitalisation is an important factor when analysing ETR trends.

Similar trends are evident regarding MNE status (see Appendix 8). MNEs tend to have higher unweighted means, in line with the findings of previous studies (Drake et al., 2020; Dyreng et al., 2008, 2017). However, the situation is reversed for weighted means for 20 of the 32 years. The negative slopes of the trendlines are also steeper, as we would expect given the difference between the unweighted and weighted ETRs from Fig. 1. The descriptive statistics suggest that the interactions of size, MNE status and digitalisation play important roles in determining cash ETRs.

5 Cash ETR and OECD digitalisation measure

5.1 Industry level digitalisation measures

The firm-level Cash ETR variable was regressed on industry level digitalisation dummies and a range of controls. The first column in Table 1 shows a number of controls, standard in the literature, for the period 1988–2019. Despite the longer time period, the size and significance of coefficients are similar to Dyreng et al. (2017) and Drake et al. (2020).

The second column includes a dummy for digital intensive industries (per OECD definition), and this moves the beginning of the sample to 2001 due to data availability for the digital intensive dummy. Here the digital intensive category dummy is marginally positive and not significant; perhaps no surprise given ETR trends outlined in the left panel of Fig. 2.

The second regression includes several control variables to account for the influence of intangible assets and prior period losses. The total amount of intangible capital is included for each firm. The share of intangible capital in total capital measures intangible intensity. The Cash ETR increases in the absolute value of intangible capital, but declines in intangible intensity.

A further four variables (NOL, NOL Delta, Five Year Loss and FCF) used in Drake et al. (2020) to estimate the probability of the use of a Valuation Allowance are included to control for prior losses. The Log of Firm Age is included as well as dummies for the Tax Cuts and Jobs Act (equal to one in 2018 and 2019) and for a firm's presence in the extractive industries (oil and mining). Industry fixed effects are not included as the variable of interest is at the industry level and does not vary over time.

Columns 3 and 4 split the data by the two economic cycles (2001–2007 and 2008–2019) to examine changes over time, if any. These periods account for the cyclical nature of ETRs, which tend to fall after recessions and rise during expansions. As the use of digital technologies becomes more prevalent over time, we may see greater negative impacts on Cash ETRs.

5.2 Digitalisation and size

Table 2 includes interaction of the OECD digitalisation dummy with three size variables representing small (< 500 employees), medium (500–4999 employees) and large (5000 + employees) firms. A summary of the main variables of interest is provided here, with the full regressions detailed in Appendix 9.

The base category in the analysis is small firms in less digital intensive industries. Over the full period (Column 1) the value of the digital dummy is positive and significant, indicating that small firms in digital intensive industries have a two percentage point higher Cash ETR than small firms in less digital intensive industries. This is reversed when it comes to the medium sized firms, however. which have a c.1% lower Cash ETR than their less digital intensive industry equivalents over the full period (the sum of the digital dummy and the Medium/Digital interaction term).

Table 2 Digital dummies with firm size interaction terms

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR
Period	'01–'19	'01–'07	'08–'19
Digital dummy OECD	0.021**	0.020	0.023*
Size medium	0.050***	0.043***	0.051***
Size medium × dig dummy	−0.030***	−0.030*	−0.028*
Size large	0.065***	0.042**	0.077***
Size large × dig dummy	−0.021*	−0.002	−0.031**
Observations	24,911	9,148	15,763
R-squared	0.081	0.095	0.080
Cluster	FIRM	FIRM	FIRM

Robust standard errors in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

Source: Authors' estimates based on Compustat data. For variable definitions see Appendix 1

Table 3 Digital dummies with MNE status interaction terms

	(1)	(2)	(3)
Dependent variable	Cash ETR	Cash ETR	Cash ETR
Period	'01–'19	'01–'07	'08–'19
Digital dummy OECD	0.012*	0.010	0.008
MNE	0.037***	0.028***	0.031***
MNE × dig dummy	-0.017**	-0.013	-0.020**
Observations	24,911	9,148	15,763
R-squared	0.078	0.092	0.076
Cluster	FIRM	FIRM	FIRM

Robust standard errors in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

Source: Authors' estimates based on Compustat data. Variable definitions provided in Appendix 1, and the full regression results are in Appendix 9

Dummies for large firms in digital intensive and less digital intensive industries are equivalent over the full period, though ETRs are c. 0.7% lower in digital intensive industries in the final cycle. We therefore have some evidence of a negative interaction between scale, digitalisation and Cash ETRs, albeit such effects are estimated as modest.

5.3 Digitalisation and MNE status

Table 3 includes interaction of the OECD Digitalisation Dummy with an MNE Dummy (zero for US only and one for MNEs). A summary of the main variables is provided in this table, with full regressions in Appendix 9.

Over the full period, MNEs in digital intensive industries have a Cash ETR 0.5% lower than MNEs in less digital intensive industries (0.012–0.017). Columns 2 and 3 split this by cycle, with the effect more pronounced in the most recent cycle. There is no statistically significant difference in the first period, but MNEs in digital intensive industries had a 1.2% lower ETR in the second period.

Overall, firms in digital intensive industries (per OECD definition) do not have lower Cash ETRs than firms in less digital intensive industries. This overall result hides some heterogeneity amongst firms in digital intensive industries. Larger firms in digital intensive industries tend to have slightly lower ETRs than equivalents in less digital intensive industries, while MNEs in digital intensive industries have slightly lower ETRs than MNEs in less digital intensive industries. Effects are modest and more pronounced in the most recent economic cycle.

5.4 The largest tech firms

Results including a dummy for the very largest tech firms (Amazon, Apple, Microsoft, Meta and Netflix) are provided in Appendix 9. Controls are the same as those used in the second regression in Table 1, and the magnitudes and statistical significance of the coefficients are almost identical. The value of the dummy suggests that for these largest firms, cash ETRs are approximately 8% lower than other firms in digital intensive industries, even when controlling for factors such as prior period losses and intangible assets. The mean Cash ETR for this group across the period from 2001 to 2019 was 17%, versus 25% for the sample as a whole. The dummy therefore reflects this gap almost exactly.

6 Robustness check

The impact of digitalisation on ETRs using BEA-based measures provides for robustness checks on our analyses. Dummies created using BEA data produced a narrower definition of digital intensive industries, with 33% of firm-year observations coming from digital intensive industries, versus 63% for the OECD measure. Estimates are provided in Appendix 10, and can be compared to results across Tables 1, 2 and 3.

The narrower BEA definition generates results indicating that digital intensive industries have an ETR that is 1.3% lower than less digital intensive industries (statistically significant at 5%). This compares to no impact from the wider OECD definition. We see the same patterns regarding size: smaller firms in digital intensive industries tend to have higher Cash ETRs relative to their less digital intensive equivalents (1.5% larger approx.); while medium and large firms have lower ETRs (2.7 and 0.8% smaller respectively). Unlike the OECD measure, both MNEs and non-MNEs in digital intensive industries have lower ETRs, as the interaction term in Regression 2 is small and insignificant. These results were not split by cycle due to the limited time-period available for the BEA-based measure.

7 Conclusions

Prompted by developments on both sides of the Atlantic—evident in discussions and adoption of digital services taxes in Europe and 2017 US tax reform targeting minimum tax on global profits—the preferences of key actors reoriented to negotiate changes in international tax rules (Young, 2024a). Simultaneously, demand to regulate 'big tech' emanated from a range of welfare discussions. These encompassed concerns over privacy regulation, competition, and harmful content (including that available to minors) such that both market making and market correcting practices, associated traditionally with the US and EU respectively, aligned (Bradford, 2023; Farrell & Newman, 2023). In the absence of evidence that supported a link between declining corporate tax revenues and increased digitalisation, the above issues seem relevant in contributing to the timing of negotiated agreement on taxation changes.

We provide our results as indicative descriptive evidence and do not imply causal relationships. Nor do our results shed light on the extent to which rationale underlying any causal relationship. While our empirical approach builds on related literature, and we include controls of relevance, there may remain unobserved characteristics for which we have not accounted driving observed correlations between firms' digital intensity and their Cash ETRs.

Our research identifies little evidence of significantly and systematically lower Cash ETRs in digital intensive industries. Nonetheless, there is heterogeneity amongst firms with larger firms in digital intensive industries tending to have slightly lower ETRs than their equivalents in less digital intensive industries. In addition, MNEs in digital intensive industries have slightly lower ETRs than MNEs in less digital intensive industries. While this may reflect the capacity to use intangible assets to lower Cash ETRs, the effects are modest. We do, however, see that the largest tech firms have considerably lower ETRs than other firms in digital intensive industries, which provides much of the impetus for corporate tax reform.

There are a number of issues that could mask more significant effects, however. The first is the potential for bias created by excluding observations with pre-tax losses. If patterns of losses vary between digital intensive and less digital intensive industries, the extent of the bias could also vary. While attempts have been made here to control for prior period losses, some bias may still remain.

In addition, we face the issue of a lack of a firm-level measure of digitalisation due to data limitations. A firm-level measure could provide for a more fine-grained measure of digitalisation and could potentially shed more light on any relationship between digitalisation and lower ETRs.

Appendix 1: Variable definitions

See Appendix 3 for details regarding BEA Digitalisation measure.

MNE is equal to one if the absolute value of pretax foreign income (PIFO in Compustat) is greater than zero or if the absolute value of foreign tax expense (TXFO) is greater than zero.

Log Assets is the natural log of total assets (AT).

R&D is the percentage of R&D expense (XRD) divided by sales (SALE).

PPE is the ratio of net property, plant, and equipment (PPENT) to total assets (AT).

Leverage is total debt (DLTT + DLC) divided by total assets (AT).

Capex is capital assets (CAPX) scaled by net property, plant, and equipment (PPENT).

Advertising is the ratio of advertising expense (XAD) to sales (SALE). If XAD is missing it is set to zero.

Special Items is the ratio of special items (SPI) to total assets (AT). If SPI is missing it is set to zero.

NOL is a dummy variable equal to one if Compustat reports a tax-loss carryforward (TLCF) at the end of the previous year.

NOL Delta is the change in net operating losses and is the difference between the current and lagged tax-loss carryforward (TLCF), scaled by lagged total assets (AT).

Five Year Loss is a count variable taking the values 0, 1, 2, 3, or 4, depending on the number of pretax losses over the years t-4 to t.

Firm size dummies—small is < 500 employees, medium is 500 – 4,999 employees and large is 5,000 + employees.

Appendix 2: Industry classification and digital taxonomy

Industry Classification and Digital Intensity Taxonomy

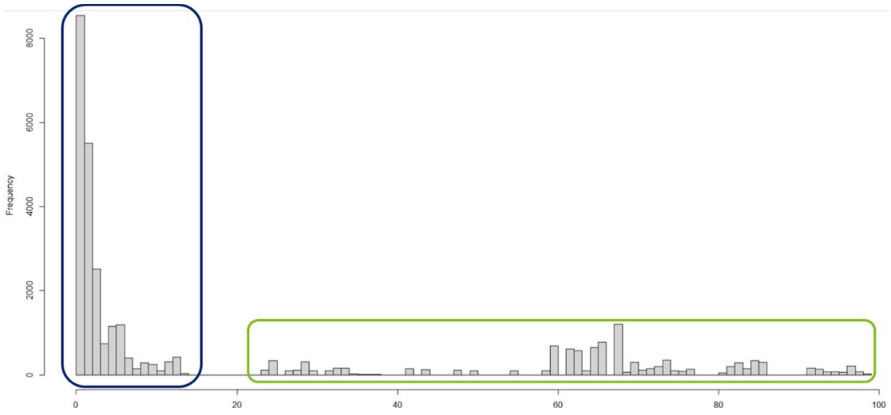
ISIC rev.4 code	Description	Digital Quartile 2001 - 2003	Digital Quartile 2013 - 2015
D10T12	Food products, beverages and tobacco [CA]	Low	Low
D13T15	Textiles, wearing apparel, leather and related products [CB]	Medium-Low	Medium-Low
D16T18	Wood and paper products, and printing [CC]	Medium-High	Medium-High
D20	Chemicals and chemical products [CE]	Medium-Low	Medium-Low
D21	Basic pharmaceutical products and pharmaceutical preparations [CF]	Medium-Low	Medium-Low
D22T23	Rubber and plastics, and other non-metallic mineral products [CG]	Medium-Low	Medium-Low
D24T25	Basic and fabricated metals, except machinery and equipment [CH]	Medium-Low	Medium-Low
D26	Computer, electronic and optical products [CI]	High	Medium-High
D27	Electrical equipment [CJ]	Medium-High	Medium-High
D28	Machinery and equipment n.e.c. [CK]	High	Medium-High
D29T30	Transport equipment [CL]	High	High
D31T33	Furniture, other manufacturing, repair of machinery and equipment [CM]	Medium-High	Medium-High
D45T47	Wholesale and retail trade, repair of motor vehicles and motorcycles [G]	Medium-High	Medium-High
D49T53	Transportation and storage [H]	Low	Low
D55T56	Accommodation and food service activities [I]	Low	Low
D58T60	Publishing, audiovisual and broadcasting activities [JA]	Medium-High	Medium-High
D61	Telecommunications [JB]	High	High
D62T63	IT and other information services [JC]	High	High
D69T71	Legal and accounting, activities of head offices, management consultancy, architecture and engineering, technical testing and analysis	High	High
D72	Scientific research and development [MB]	Medium-High	High
D73T75	Advertising and market research, other professional, scientific and technical activities, veterinary activities [MC]	High	High
D77T82	Administrative and support service activities [N]	High	High

Source: Calvino et al. (2018)

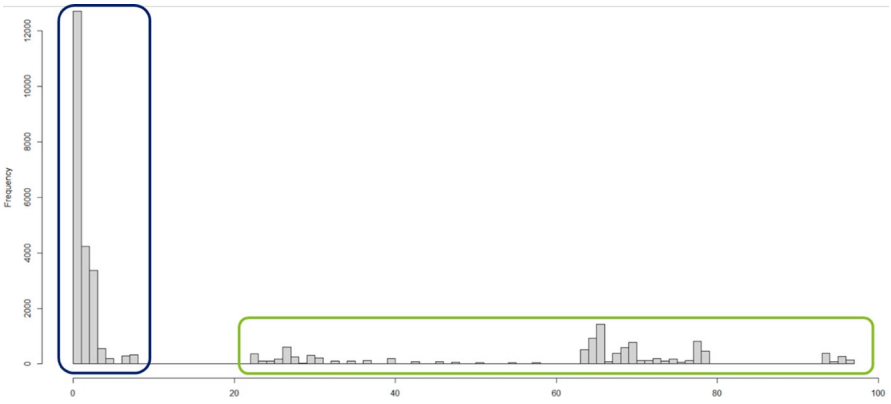
Appendix 3: US BEA digitalisation measures

Estimates of digitally derived gross output, value added, employment, and compensation are provided for 92 NAICS industries. Histograms outlining each industry/year value for all three categories are provided below. As with the OECD data, the industries are split into 'less digital' and 'more digital' categories. We can see two distinct clusters of industries in each category. The first group tends to have 10% or less of value added/employment/compensation defined as 'digital'. They are designated as being 'less digital', and marked in blue below. The second group has at least 20%, and are designated as 'more digital' (marked in green).

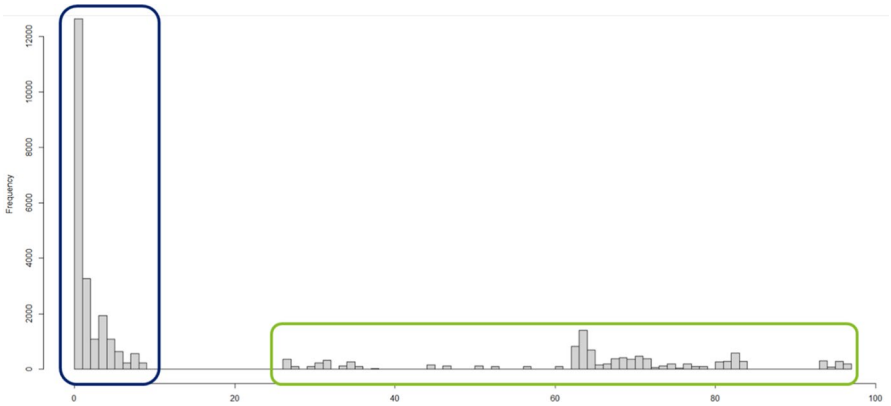
Value added



Employment



Total compensation



Appendix 4: Intangible asset accumulation parameters

The table below is taken from Ewens et al. (2021) and summarises the key intangible capital accumulation parameters. Columns 2 and 3 outline the assumptions used by Peters and Taylor (2017). Column 1 shows the fraction of SG&A expenses that are assumed to constitute intangible investment rather than current period expenses. Column 2 shows the assumptions for the depreciation rate of R&D by industry, following Li and Hall (2020).

Columns 3 and 4 show the equivalent estimates in Ewens et al. (2021).

All parameters used in calculating firm-level intangible capital in this study are taken from Ewens et al. (2021).

Industry	Peters and Taylor (2017)		Ewens et al. (2021)	
	SG&A investment	R&D Dep. rate	SG&A investment	R&D Dep. rate
All	0.30	0.28	0.27	0.33
Consumer	0.30	0.31	0.19	0.33
Manufacturing	0.30	0.25	0.22	0.42
High Tech	0.30	0.31	0.44	0.46
Health	0.30	0.18	0.49	0.34
Other	0.30	N/A	0.34	0.30

Appendix 5: Sample selection criteria

Source: Author calculations from Compustat data

Criterium	Number of firms	Firm-years
All nonfinancial, non-utilities Compustat observations between 1988 and 2019 with assets greater than $10 million	16,889	161,698
Require non-missing values for cash tax paid (TXPD)	14,200	134,344
Require pretax income (PI) of greater than zero	11,463	92,562
Require non-negative values for sales, cost of goods sold and sales, general and administrative expenses	10,716	85,346
Require non-missing values for controls (PPENT, INTAN, LEVERAGE, CAPEX, ADS)	10,276	77,254
Require non-missing Peters & Taylor intangible values and remove small number (c. 300) of duplicate observations	10,119	76,369

Appendix 6: Deflating the data

Deflators for gross output, labour costs and intermediates were obtained from BEA, while deflators for fixed capital were taken from OECD STAN. We adopted a principal of using the most granular deflator available for each variable.

Gross output

Deflator data are available from BEA providing, at the summary level, (102 unique deflators) for years before 1997. These deflators correspond to industries at various levels of granularity (industries at the 2, 3 and 4-digit levels in the NAICS system).

We then match these deflators with the appropriate firms in the Compustat data using the NAICS codes corresponding to each deflator. The NAICS codes in Compustat are purely numeric, whereas some NAICS codes also contain letters. For example, BEA gives a deflator for "Motor vehicles, bodies and trailers, and parts" which corresponds to NAICS code 3361MV. A 3361 code will not identify all companies under this code, as one category under this heading is classified as 3362BP (which is in turn made up of codes beginning with 3362 and 3363). Therefore, the deflator is matched to three possible codes – 3361, 3362 and 3363. There are therefore cases where different NAICS codes have common deflators (for example different 4-digit codes can have the same 3-digit code in common), but two separate deflators cannot refer to the same NAICS code.

About 83% of Compustat observations have a six-digit code, though there are some companies with 5, 4, 3 and even 2-digit codes. They are generally larger companies spanning multiple areas (for example Kraft is 311—Food Manufacturing).

The first step is therefore to link all of the 2–4-digit codes with their equivalent deflators. Our approach involved shortening the 6-digit Compustat codes to the lowest level of aggregation where a match can be found. We shortened the Compustat codes to their first 4 digits, leaving 415 unique codes. These codes were mapped to the relevant deflators at the 2, 3 and 4-digit level, using the highest degree of granularity possible. For example, if the code had 4 digits, it would be matched with its corresponding 3-digit code if no code existed with a deflator at the 4-digit level.

Data with no NAICS code

No NAICS code was provided for about 10% of the Compustat observations. Each observation did have an SIC code however, and so the SIC codes were matched to appropriate NAICS Codes using the 'SIC to NAICS Crosswalk' from www.naics.com. Some of the Compustat codes did not appear on this list, and the additional industries were identified from a list provided by the SEC (https://www.sec.gov/info/edgar/siccodes.htm). These could then be matched to NAICS codes by the process above.

Some SIC codes could refer to multiple NAICS codes. Where each of these codes had a common higher-level deflator, the most granular higher level deflator was used. For example, SIC code 119 (Cash Grains, Nec) could refer to any of the 6 NAICS codes from 111,120 to 111,199. The code was therefore matched to NAICS code 1111.

In some cases the SIC code could refer to multiple NAICS codes, at least some of which did not have a more granular 3 or 4 digit code in common. Here the similar procedures were used when matching NAICS and NACE codes (see the section on Mapping NAICS and NACE/ISIC Codes below).

- Where the name of the SIC code closely matched one of the NAICS codes, that NAICS code was used.
- If there was a majority of codes with the same 3 or 4 digits in common this deflator was used, otherwise we employed a common 2-digit deflator.
- If there were only 2 mappings and it the decision was not obvious based on the names, then the code which fitted most closely with the surrounding SIC/NAICS matches was kept. For example, SIC Code 752 (Animal Specialty Services) could match with NAICS codes 115,210 (Support Activities for Animal Production) or 812,910 (Pet Care (except Veterinary) Services). All the matches around the code.

A small number of codes present in Compustat (4888, 6020, 6797, 8400 and 9997) were not identified in either the NAICS or SIC lists, so these codes were not matched to a deflator.

The NAICS codes in the SIC-NAICS code pairs were shortened to a maximum of 4-digits. There were 21 additional unique 4-digit NAICS codes to add to the 415 above. These were then matched with appropriate deflators as per the process above.

Labour cost deflators

The BEA provides data on labour compensation as well as a labour quantity index for 63 industry segments (at the 2, 3 and 4-digit level). Separate data is available for college and non-college educated labour. The labour compensation data is divided by the labour quantity indices to arrive at a series of labour price deflators for both college and non-college educated labour. It is then rebased with 2012 equal to 100 in order to match the other deflators. We then combine the two indices into one overall labour price index by weighting the college and non-college educated indices by their shares of total labour compensation.

Each of the 63 deflators are then matched to the Compustat data using the same process outlined above. In a small number of cases we do not have deflators at the 2-digit level. Where this occurs, we create the deflators by combining deflators at lower levels of granularity, weighted by their shares of gross output. For example, no wage and quantity data is provided for Agriculture, Forestry, Fishing, and Hunting (NAICS 11). However, we have two deflators for the sub-indices of Farms (111CA) and Forestry, Fishing, and Related Activities (113FF). These indices are combined using their respective shares of gross output in each individual year to provide a deflator for NAICS 11.

The data begins in 1987, and the years before are proxied by the corresponding intermediates deflator. The average correlation between the intermediates deflators and the labour cost deflators is 0.90 for the years after 1987 (standard deviation 0.12). This is higher than the average correlation with the output deflator (0.81), and so the intermediates deflator is preferred.

Intermediate cost deflators

Deflators for intermediates are available at the Summary level only for years before 1997. Furthermore, some deflators at the Summary level are only available from 1998 on. Where this is the case, the deflator was matched to a higher level deflator in order to provide a continuous series going back to the 1960s.

Using intermediate and labour deflators to create opex and intangible deflators

Opex

Each firm's operating expenses (COGS and SG&A) are made up of intermediate costs (such as energy, materials and services) and labour costs. Compustat does not provide separate data for materials and labour costs, and so we rely on BEA KLEMS data to calculate the proportion of intermediate and labour costs by industry. BEA KLEMS data provides data on compensation to energy, materials and services, as well as college and non-college labour for 63 industries from 1987 to 2019. The intermediate and labour cost deflators are then weighted in

these proportions, with separate weights calculated for each of the 63 industry categories in each year.

For years before 1987 no separate labour deflators are available. As noted above, the labour deflators are proxied by the corresponding intermediate deflator. The Opex deflator is therefore the same as the intermediates deflator for the years before 1987.

Intangibles

The inputs to the creation of intangible assets will be a combination of labour, materials and services. Unfortunately, there is no way of knowing the proportions for individual firms. The intangible deflator was therefore created by averaging the relevant labour and intermediate deflators for each industry.

Deflating fixed capital

Deflators for fixed capital by industry were obtained from the OECD STAN database. The industries are classified according to the NACE classification system, and so each deflator was matched to the relevant NAICS industry code. A conversion table provided by Eurostat was used for the matching process, with further details below.

In some cases, a two-digit NAICS deflator could refer to more than one two-digit NACE deflator. For example, NAICS 21 (Mining) could refer to NACE 5, 6, 7, 8 or 9. Some of these deflators could be matched to a higher-level NACE deflator. For instance, in the case above, NAICS 21 corresponds to NACE D05T09 (Mining and quarrying). Where no such higher-level deflator existed, we used a weighted average of the matching industry deflators, with separate weights for each year based on the nominal gross output of the relevant industries.

Mapping NAICS and NACE/ISIC codes

NAICS codes from Compustat (mainly at the 6 digit level) were mapped to 2 digit NACE Rev 2 codes using mappings from Eurostat here. Most codes were from NAICS 2017, but some were from earlier iterations, and appropriate mappings were added for these earlier codes.

In some cases, there was more than one potential mapping and judgement was used to eliminate conflicts. Considerations used were:

1. The similarity of the names from the NAICS to ISIC/NACE mapping. In the example below, the mapping to ISIC/NACE 5 was removed.

211,130	Natural Gas Extraction	*	5	510	Mining of hard coal
211,130	Natural Gas Extraction		6	620	Extraction of natural gas

2. If there were 3/4 mappings of a NAICS code to an ISIC/NACE and all but one referred to the same 2 digit ISIC/NACE code, then the code with the majority of the mappings was kept. See example below where ISIC/NACE 3 was removed.

111,419	Other Food Crops Grown Under Cover	*	1	113	Growing of vegetables and melons, roots and tubers
111,419	Other Food Crops Grown Under Cover	*	1	122	Growing of tropical and subtropical fruits
111,419	Other Food Crops Grown Under Cover	*	1	128	Growing of spices, aromatic, drug and pharmaceutical crops
111,419	Other Food Crops Grown Under Cover	*	3	322	Freshwater aquaculture

3. If there were only 2 mappings and it the decision was not obvious based on the names, then the code which fitted most closely with the surrounding ISIC/NACE codes was kept. For example, in the case below for ISIC code 325992 all surrounding codes referred to SIC/NACE 2-digit code 20. Therefore we kept the mapping to code 20 and dropped the mapping to 28.

325,991	Custom Compounding of Purchased Resins	20	2013	Manufacture of plastics and synthetic rubber in primary forms
325,992	Photographic Film, Paper, Plate, and Chemical Manufacturing	20	2029	Manufacture of other chemical products n.e.c
325,992	Photographic Film, Paper, Plate, and Chemical Manufacturing	28	2817	Manufacture of office machinery and equipment (except computers and peripheral equipment)
325,998	All Other Miscellaneous Chemical Product and Preparation Manufacturing	20	2011	Manufacture of basic chemicals

4. NAICS distinguishes stores by whether they are involved in retail or repair. Where such conflicts arose, the stores were classified as retail, under the assumption that the majority of business for these stores is retail rather than repair.

Less than 10% of Compustat observations did not have NAICS codes, but did have SIC codes. Only 3 SIC codes appeared after 1985–5944, 6722 and 6726. These were mapped to NAICS codes 448,310, 525,910 and 525,990 respectively, which in turn were mapped to NACE codes 95, 64 and 64.

Appendix 7: Summary statistics

Source: Authors' estimates based on Compustat data. NOL is net operating loss, FCF is free cash flow, MNE is multinational Enterprise and TCJA is the Tax Cuts and Jobs Act

Variable	N	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Cash ETR	76,369	0.27	0.24	0.09	0.24	0.37
Log sales	76,369	6.22	2.05	4.73	6.16	7.62
Log assets	74,669	6.22	1.97	4.71	6.10	7.58
R&D	75,065	0.03	0.05	0.00	0.00	0.03
PPE	74,374	0.27	0.22	0.10	0.21	0.38
Leverage	75,101	0.22	0.19	0.04	0.20	0.34
Capex	74,244	0.26	0.17	0.14	0.21	0.34
Advertising	74,640	0.01	0.02	0.00	0.00	0.01
Special items	74,483	0.00	0.02	0.00	0.00	0.00
Lag special items	69,995	−0.01	0.03	−0.01	0.00	0.00
NOL	76,369	0.37	0.48	0.00	0.00	1.00
NOL delta	50,057	−0.03	6.55	0.00	0.00	0.00
Five year loss	76,369	0.56	0.96	0.00	0.00	1.00
FCF	71,910	0.25	68.88	0.00	0.05	0.10
MNE	76,369	0.52	0.50	0.00	1.00	1.00
Total intangibles	76,369	5.13	2.18	3.52	5.01	6.61
Intangible share	75,240	0.62	0.28	0.42	0.68	0.86
Log age	76,279	2.89	0.76	2.40	2.83	3.26
TCJA	76,369	0.05	0.22	0.00	0.00	0.00
Extractive dummy	76,369	0.06	0.24	0.00	0.00	0.00
Digital dummy OECD	44,795	0.63	0.48	0.00	1.00	1.00
Digital dummy BEA	34,724	0.33	0.47	0.00	0.00	1.00

Appendix 8: Mean and weighted mean cash ETRs split by MNC status

Source: Authors' estimates based on Compustat data.

Appendix 9: Cash ETR regressions with OECD digitalisation measure

OECD industry level digitalisation measure

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR	(4) Cash ETR
Period	'88–'19	'01–'19	'01–'07	'08–'19
Digital dummy OECD		0.002	0.009	−0.001
MNE	0.025***	0.026***	0.023***	0.029***
Trend	−0.003***	0.000	0.004***	0.000
Log sales	0.023***	0.015***	0.022***	0.010**
Log assets	−0.017***	−0.049***	−0.055***	−0.045***
R&D	−0.274***	−0.318***	−0.214***	−0.355***
PPE	−0.126***	−0.178***	−0.150***	−0.198***
Leverage	−0.021**	−0.027**	−0.012	−0.034**
Capex	−0.053***	−0.044***	−0.035**	−0.053***
Advertising	0.088	0.109	0.381***	−0.015
Special items	−1.941***	−1.520***	−1.434***	−1.556***
Lag special items	0.256***	0.035	0.185	−0.019
NOL	−0.061***	−0.041***	−0.048***	−0.033***
NOL delta	0.000	−0.000	0.007	−0.000
Five year loss		−0.015***	−0.024***	−0.008***
FCF		−0.000	−0.004	0.000
Book intangibles	0.030***			
Total intangibles		0.039***	0.036***	0.040***
Intangible share		−0.123***	−0.126***	−0.124***
Log age		0.009***	0.008	0.008**
TCJA		−0.028***		−0.027***
Extractive dummy		0.038***	0.021	0.047***
Observations	42,540	24,911	9,148	15,763
R-squared	0.094	0.078	0.092	0.075
Cluster	FIRM	FIRM	FIRM	FIRM

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$OECD digitalisation and size

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR
Period	'01–'19	'01–'07	'08–'19
Digital dummy OECD	0.021**	0.020	0.023*
Size medium	0.050***	0.043***	0.051***
Size medium × dig dummy	−0.030***	−0.030*	−0.028*
Size Large	0.065***	0.042**	0.077***

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR
Size large × dig dummy	−0.021*	−0.002	−0.031**
MNE	0.024***	0.021***	0.027***
Trend	0.001	0.004***	0.000
Log sales	0.009**	0.018***	0.003
Log assets	−0.044***	−0.051***	−0.039***
R&D	−0.290***	−0.185***	−0.328***
PPE	−0.169***	−0.144***	−0.187***
Leverage	−0.022*	−0.008	−0.029**
Capex	−0.047***	−0.036**	−0.057***
Advertising	0.107	0.404***	−0.029
Special items	−1.508***	−1.425***	−1.543***
Lag special items	0.041	0.190*	−0.011
NOL	−0.043***	−0.049***	−0.036***
NOL delta	−0.000	0.006	−0.000
Total intangibles	0.032***	0.031***	0.032***
Intangible share	−0.100***	−0.105***	−0.101***
Log age	0.008**	0.007	0.007**
TCJA	−0.029***		−0.028***
Extractive dummy	0.048***	0.030*	0.058***
Observations	24,911	9,148	15,763
R-squared	0.081	0.095	0.080
Cluster	FIRM	FIRM	FIRM

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$OECD digitalisation and MNE status

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR
Period	’01–’19	’01–’07	’08–’19
Digital dummy OECD	0.012*	0.010	0.008
MNE	0.037***	0.028***	0.031***
MNE × dig dummy	−0.017**	−0.013	−0.020**
Trend	0.001	0.004***	−0.001
Log sales	0.015***	0.024***	0.020***
Log assets	−0.048***	−0.052***	−0.045***
R&D	−0.312***	−0.225***	−0.282***
PPE	−0.174***	−0.120***	−0.150***
Leverage	−0.028**	−0.034**	−0.067***
Capex	−0.044***	−0.015	−0.035**
Advertising	0.103	0.396***	0.056
Special items	−1.523***	0.523***	0.307***
Lag special items	0.035	0.329***	0.071

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR
NOL	−0.041***	−0.051***	−0.035***
NOL delta	−0.000	0.008	−0.000*
Five year loss	−0.015***	−0.029***	−0.016***
FCF	−0.000	−0.003	0.000
Total intangibles	0.038***	0.031***	0.028***
Intangible share	−0.119***	−0.095***	−0.091***
Log age	0.009***	0.007	0.009***
TCJA	−0.028***		−0.021***
Extractive dummy	0.039***	0.023	0.038***
Observations	24,911	9,148	15,763
R-squared	0.078	0.092	0.076
Cluster	FIRM	FIRM	FIRM

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$Dummy for the largest tech firms

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR
Period	'01–'19	'01–'07	'08–'19
Digital dummy OECD	0.002	0.010	−0.000
Large tech	−0.083***	−0.082***	−0.076***
MNE	0.022***	0.017**	0.026***
Trend	0.001	0.004***	0.000
Log sales	0.013***	0.021***	0.009*
Log assets	−0.046***	−0.050***	−0.043***
R&D	−0.351***	−0.230***	−0.397***
PPE	−0.158***	−0.130***	−0.176***
Leverage	−0.031***	−0.022	−0.036**
Capex	−0.041***	−0.034*	−0.050***
Advertising	0.104	0.365***	−0.015
Special items	−1.665***	−1.426***	−1.792***
Lag special items	0.027	0.105	−0.003
NOL	−0.041***	−0.047***	−0.035***
NOL delta	−0.000	0.006	−0.000
Five year loss	−0.020***	−0.027***	−0.015***
FCF	−0.000	−0.004	0.000
Total intangibles	0.038***	0.034***	0.039***
Intangible share	−0.100***	−0.096**	−0.104***
Log age	0.009***	0.006	0.010**
TCJA	−0.043***		−0.040***
Extractive dummy	0.024**	0.015	0.031**
Observations	23,506	8,890	14,616

Dependent variable	(1) Cash ETR	(2) Cash ETR	(3) Cash ETR
R-squared	0.085	0.095	0.083
Industry FE	NO	NO	NO

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 10: Cash ETR regressions with BEA based digitalisation measure

BEA based industry level digitalisation measure

Dependent variable	(1) Cash ETR
Period	'05–'19
Digital dummy BEA	−0.013**
MNE	0.027***
Trend	−0.001
Log sales	0.014***
Log assets	−0.049***
R&D	−0.318***
PPE	−0.165***
Leverage	−0.023*
Capex	−0.053***
Advertising	0.064
Special items	−1.502***
Lag special items	0.016
NOL	−0.039***
NOL Delta	−0.000
Five year loss	−0.011***
FCF	−0.000
Book intangibles	
Total intangibles	0.039***
Intangible share	−0.105***
Log age	0.009**
TCJA	−0.023***
Extractive dummy	0.034***
Observations	19,808
R-squared	0.078
Cluster	FIRM

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

BEA based digitalisation and size

Dependent variable	(1) Cash ETR
Period	'05–'19
Digital dummy BEA	0.015
Size medium	0.054***
Size medium × dig dummy	−0.042***
Size large	0.068***
Size large × dig dummy	−0.023*
MNE	0.025***
Trend	−0.001
Log sales	0.008*
Log assets	−0.043***
R&D	−0.286***
PPE	−0.154***
Leverage	−0.016
Capex	−0.057***
Advertising	0.070
Special items	−1.492***
Lag special items	0.024
NOL	−0.042***
NOL delta	−0.000
Total intangibles	0.032***
Intangible share	−0.082***
Log age	0.007**
TCJA	−0.024***
Extractive dummy	0.045***
Observations	19,808
R-squared	0.083
Cluster	FIRM

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

BEA based digitalisation and MNE status

Dependent variable	(1) Cash ETR
Period	'05–'19
Digital dummy BEA	−0.018*
MNE	0.025***
MNE × dig dummy	0.008
Trend	−0.001
Log Sales	0.014***
Log Assets	−0.049***

Dependent variable	(1) Cash ETR
R&D	−0.323***
PPE	−0.166***
Leverage	−0.023*
Capex	−0.054***
Advertising	0.062
Special items	−1.500***
Lag special items	0.016
NOL	−0.039***
NOL delta	−0.000
Five year loss	−0.011***
FCF	−0.000
Total intangibles	0.039***
Intangible share	−0.106***
Log age	0.009**
TCJA	−0.023***
Extractive dummy	0.034**
Observations	19,808
R-squared	0.078
Cluster	FIRM

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Declarations

Conflict of interest The authors declare no competing interests.

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