An occupation and asset driven approach to capital utilisation adjustment in productivity statistics

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Abstract

The coronavirus pandemic exposes some fundamental shortcomings in the accepted methods used to estimate productivity, notably the failure to adjust for variations in the utilisation of capital. In a time of national lockdown, the consequent introduction of furloughing (workers away from jobs but still being paid) and a massive shift to homeworking, capital utilisation is expected to fall rapidly. Official measures of productivity, including those produced by the UK Office for National Statistics (ONS), have not historically taken into account variations in capital utilisation over time. In this case, Multi-Factor Productivity (MFP) appears to fall too far, since measured capital input is near constant. There is no internationally agreed method to adjust for capital utilisation; although the literature offers a number of options, none are widely accepted due to conceptual, data availability and data quality issues. We offer an extension to an existing approach of using labour hours worked as a proxy for capital hours worked, overcoming conceptual issues by matching worker types (occupations) to capital types (assets). We use data from the US O*NET database, mapped to UK occupation codes, to inform the matching of UK occupation codes to assets, then measure the hours worked of those occupations relative to usual in order to measure deviations in capital utilisation by asset. We also introduce a conceptual framework to apply these adjustments, noting that not all assets will be subject to variation in utilisation to the same degree. We test a number of sensitivities in the methods, including methods to construct the baseline and the degree of variation allowed for each asset. Our central estimate shows a decline in capital utilisation of around 9% in the UK market sector in the height of the pandemic, recovering over half of this by the end of 2020. This subdues, but does not eliminate, the fall in MFP through 2020.

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1. Introduction

Standard[1] measures of Multi-Factor Productivity (MFP) combine changes in capital and labour inputs (weighted by their shares of income), subtracted from changes in production output, to leave changes in MFP by residual. Output is typically measured as Gross Value Added (GVA) in real terms (after accounting for price changes); labour inputs are typically hours worked, or persons employed, and sometimes account for labour composition; and capital is typically measured using a capital services index. Capital services indices weight together changes in the productive capital stock, where the weights are given by user costs (approximately equal to rental prices), rather than their shares of value in the total capital stock.

The user costs are derived using a standard formula, accounting for depreciation of the asset, price changes of the asset, and a rate of return on capital. The effect is to give more weight to faster depreciating capital – assets with shorter assets lives, such as ICT hardware and intangibles – which are used more intensively in production, but have a smaller weight in the capital stock. Conversely, assets with longer asset lives that depreciate slowly – such as buildings and structures – while making up a large fraction of the value of the capital stock, are weighted relatively less in the capital services index, since they are used less intensively in production.

While the user cost weights modify the capital stock to be more appropriate as a measure of productive input, they nonetheless show the *potential* flow of capital services, rather than the actual flow. Of course, actual capital input is generally unobservable, and so capital services are usually considered to be a sufficient approximation. By contrast, the actual flow of labour services is observable, measured as the hours actually worked of employed persons. Where productivity measures use hours actually worked as the labour input, and capital services not adjusted for utilisation as the capital input, there is some inconsistency in approach, although this is likely a reasonable assumption in normal times.

It is likely that at all times of the business cycle, capital is not used to its full potential. During negative economic shocks, instead of selling off or scrapping capital assets, businesses may instead opt to reduce their utilisation of these assets. By not adjusting the capital services index to account for this fall in utilisation, capital usage appears greater than the true usage, which biases upward the capital services measure, and hence biases down the MFP measure; this introduces procyclicality into MFP.

As discussed at greater length in Section 2, there is a school of thought that productivity should not be adjusted for capital utilisation, for one of two reasons. Either due to the philosophical view that reduced capital utilisation *is* a fall in productivity, or on the assumption that other parts of the capital services model will adapt appropriately to a change in utilisation of capital, rendering an adjustment unnecessary. We believe these views are inconsistent with current measurement.

In the case of the philosophical argument, labour input measured by hours worked (as is typical) already accounts for labour utilisation. To be consistent with the view that reduced utilisation of the factors of production (labour and capital) is a drop in productivity, labour should instead be measured as potential input: as a headcount measure (equivalent to capital services).

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[1] A fuller description of the methods used in growth accounting by many National Statistical Institutes, including the UK ONS, are given in the OECD Manual on Measuring Productivity (OECD, 2001). We also recommend the “Simple guide to MFP” from the ONS (ONS, 2018).

In the case of the model-response view, this is likely only true in the medium term, once economic actors have had a chance to respond, and the data inputs also respond. Since capital investment is by definition a long-term venture, firms are unlikely to sell or scrap assets in response to short shocks, and if the assets are unwanted by one firm, the chance of them being demanded by others is likely to also be low. So, while investment may fall in the short run, and in turn capital stocks may slowly fall in the medium run, it takes a reasonable time before the capital stock shifts to respond. As a result, capital services will react slowly, rendering this measurement unresponsive in the short run to shocks.

In addition, parts of MFP measurement in most National Statistical Institutes (NSIs), including UK Office for National Statistics (ONS), rely on assumptions and parameters that do not vary over time, such as asset lives, or are simply unmeasured, such as capital scrappage. As such, short term movements in capital utilisation are very unlikely to be captured in current measures, at least in the short-run.

As such, we view some merit in adjusting for capital utilisation in the short run, especially in times of shocks and structural breaks – the coronavirus pandemic clearly presents such an occasion. We present some options for implementation in Section 6.

The paper proceeds as follows. In Section 2, we provide a review of the literature on how to adjust for capital utilisation. In Section 3, we present our modification to the utilisation adjustment, and describe how we will carry it out. Section 4 briefly describes the data and methods to estimate our utilisation series. Section 5 provides some brief analysis of the results, and comparisons against other measures. Section 6 concludes and presents some options for implementation in NSIs.

2. Literature review

The reason that no NSIs, to our knowledge, implement a capital utilisation adjustment into their regular productivity statistics is that it is difficult to measure to a reliable standard. The OECD Manual on Measuring Productivity (OECD, 2001) states that while accounting for utilisation can explain some of the procyclical nature of productivity calculations, variations in in the utilisation of capital inputs are ineffectively measured and so there is no generally accepted approach. There is, however, some literature on potential methods.

On reviewing the literature, we recognise four main strands:

1. Model capital utilisation ex-post, based on observed output, estimated capital stock (and/or capital investment) and calibrated parameters on the relationships between these variables
2. Using labour hours worked as a proxy, on the assumption that capital must be used by workers and therefore changes in worker hours also reflect changes in capital hours[2]
3. The use of survey-based measures of capital utilisation, particularly for manufacturing industries, such as that carried out by the Confederation of British Industry (CBI) in the UK
4. The 'model adjustment' philosophy

We take each of these in turn.

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[2] We also note literature on other input-based proxies such as energy usage and materials usage, such as Burnside, Eichenbaum and Rebelo (1995). These are generally relevant only to parts of the economy, notably manufacturing. See also Bils and Cho (1994). Since they do not have wide application, we do not review them in detail here.

2.1. Model-based approaches

Larsen, Neiss and Shortall (2001) build on Burnside and Eichenbaum's (1994) work with a more focused look to derive a series for capital utilisation and labour effort in the UK to create an improved estimate for total factor productivity (TFP) that accounts for variable factor utilisation. Their measure of utilisation U^t is shown in the equation below, where K_t is the capital stock at time t, Y_t is real output at time t, α is the share of labour in income, δ is the steady-state depreciation rate, and ϕ is the elasticity of depreciation with respect to utilisation.

$$U^t = \left[\frac{(1-\alpha)}{\delta\phi}\frac{1}{\left(\frac{K_t}{Y_t}\right)}\right]^{\frac{1}{\phi}}$$

The method used for capital utilisation is a rearrangement of Burnside and Eichenbaum's (1994) model such that the capital-to-output ratio is more obvious. From this we can see that when the capital-to-output ratio is low, the capital utilisation rate is high – when there is less capital available, relative to output, it must be used more intensively. Put another way, when utilisation is high, the firm must invest in more capital to expand production, raising the capital stock and reducing the relative utilisation rate. Higher utilisation could therefore be seen to lead investment, as noted in Shapiro, Gordon and Summers (1989).

Another key take away from Shapiro *et al.* (1989) is the issue raised about the inherent difficulty in measuring capital utilisation since it is not directly observable and is therefore subject to substantial measurement error. They therefore suggest that capital utilisation calculations should be sector-specific.

Both Burnside and Eichenbaum (1994) and Larsen, Neiss and Shortall (2001) derive a series for capital utilisation which track survey-based measures for capacity utilisation[3] reasonably well. The correlation between both papers' capital utilisation measures and survey measures indicates the validity of the framework for modelling capital utilisation. It is worth noting that both sets of survey data cover only manufacturing industries, whereas the Larsen, Neiss and Shortall implementation of the model covers the whole economy, so the result may not be generalisable. This reiterates the problems mentioned by Shapiro *et al.* that measurements must often be sector-specific, meaning that methods for generating capital utilisation estimates in manufacturing may not always be easily transferred to non-manufacturing sectors.

There is also an important distinction between *capacity utilisation* (covering all factors of production, including labour) and *capital utilisation*. Survey measures, which generally ask about *capacity utilisatio*n, will reflect to at least some degree the utilisation of labour. Where the utilisation of labour and capital differ (for the reasons we set out in Section 3.2) this makes survey-based *capacity utilisation* measures imperfect measures of *capital utilisation*. However, due to a lack of appropriate comparable benchmarks, comparing to such surveys is common in the literature.

Larsen, Neiss and Shortall's measure of annual TFP growth displays peaks and troughs in line with the economic cycle and by accounting for variable factor utilisation, the standard deviation of TFP growth is reduced by about 50%, which 'explains' (removes) some of the procyclicality observed in TPF estimates that do not adjust for varying capital utilisation.

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[3] The Confederation of British Industry (CBI) and British Chamber of Commerce (BCC) surveys in the UK, and figures from the Federal Reserve in the US.

2.2. Hours-based approach

An alternative proxy for capital utilisation is to use hours worked per worker, as developed by Foss (1981), Basu and Kimball (1997), Basu, Fernald and Shapiro (2001), and Gorodnichenko and Shapiro (2011)[4]. The underlying assumption is that workers are required to work capital, and so if labour works less, the capital will work less. In this sense, the capital and labour measures gain a symmetry: the labour measure is the stock of labour (employment) multiplied by a utilisation rate (average hours worked per worker); likewise, the capital measure is the stock of capital multiplied by a utilisation rate (also average hours worked per worker).[5]

Basu and Kimball (1997), using a dynamic model under various assumptions, suggest that fluctuations in hours worked per worker are proportional to unobserved changes in both labour effort and capital utilisation. This leads to their view that hours worked per worker, while intended to represent labour effort, can also be used as a proxy for capital utilisation.

Goodridge, Haskel and Wallis (2013) implement the work of Basu, Fernald and Kimball (2006), an extension of Basu and Kimball (1997), and comment on the effect of capital utilisation adjusted TFP in the UK. They find that during the 2007-2008 financial crisis, using an hours per worker proxy does lead to a TFP value higher than official TFP measures[6]. While this does indicate that adjusting for capital utilisation can 'explain' some of the fall in TFP during this period and therefore reduce some of the pro-cyclicality in the series, they observe that the contribution of utilisation is considerably less than seen in the US.

The hours approach is considered to be the most promising and is implemented in TFP estimates for the US by John Fernald (e.g. Fernald, 2014). However, it is not internationally agreed, and the OECD Measuring Productivity Manual, while acknowledging its potential, does not recommend implementing it.

2.3. Survey-based approaches

In more recent literature, Comin *et al.* (2020) propose an estimation method that relies on a survey-based utilisation proxy: specifically, responses from firms on their current capacity utilisation given as a percentage.[7] Note again that this relates to *capacity utilisation* (including utilisation of other factors of production, including labour), rather than specifically *capital utilisation* (utilisation of only fixed capital assets), and these are likely to differ.

Comin *et al.* (2020) reiterate an issue with the hours-based approach described in Section 2.2: that hours worked per worker can change for reasons not related to utilisation. They seek to avoid this problem by using information specifically related to a business' perceived own capacity utilisation.

Comin *et al.* (2020) show that in the UK using hours worked per worker as a proxy for utilisation delivered "insignificant and counterintuitive results" which may be attributed to

[4] Gorodnichenko and Shapiro (2011) discuss some different interpretations of using hours as a capital utilisation proxy e.g. using labour hours, number of shifts, number of temporary workers employed.
[5] Burnside, Eichenbaum and Rebelo (1995) use energy as a proxy for capital utilisation following the assumption that increased usage (increased utilisation) of machinery would require more energy. They find a strong correlation between hours worked and electricity use in some manufacturing industries but not all, but find that the correlation between output and hours is more consistent across manufacturing industries.
[6] Official MFP measures from the UK ONS have been revised considerably since then.
[7] In the UK this question, in the CBI business survey, is: "What is your current rate of operation as a percentage of full capacity?" See Lee, Mahony and Mizen (2020) for an account of the CBI business surveys.

hours worked per worker fluctuating due to reasons unrelated to utilisation. This is something we seek to improve upon in our method.

To summarise, the above papers and methods represent some of the main literature surrounding capital utilisation and at what level of accuracy it can be calculated. A consistent theme in the literature is that by adjusting for variable utilisation, TFP growth is less pro-cyclical. Our contribution to this literature is to implement a new method for calculating capital utilisation. We do so by taking a much more granular look into using hours worked by accounting for occupation types and therefore the capital types used by different roles, in order to produce a more informed capital utilisation adjustment.

2.4. The 'model response' philosophy

One contrary interpretation of productivity is that an underutilisation of capital *is* a drop in productivity. A failure to fully utilise the capital of an industry would be interpreted as a fall in productivity of that industry. In many other situations, that would seem appealing – frictions in business structures that prevent effective utilisation of assets could indeed be interpreted as a productivity loss, and improvements that allow for increased utilisation could indeed be thought of as a productivity gain. This interpretation likely works well in 'normal times'. However, it seems unintuitive during the coronavirus pandemic, when an inability to use capital is *not* as a result of business inefficiency, but rather exogenous factors. The drop in output with respect to available capital input here could be thought of as theoretical spare capacity driven by weak demand, unexpectedly poor market conditions, or some unexpected shock. In this situation, it would seem perverse to label this as a fall in productivity, rather than a fall in measured inputs. It does however reflect a somewhat philosophical debate on the meaning of productivity.

Moreover, in the medium term, the other components of the growth accounting framework should adjust, such that changes to the demand for capital are accounted for. For instance, if office buildings are less beneficial to businesses after the pandemic, then the stock of buildings will shrink through reduced investment and increased scrappage. Put another way, the rate of return on buildings will fall (relative to other options) and as a result the supply of buildings will fall to re-introduce equilibrium to the asset market. This will reduce capital services due to a negative growth of the productive stock. It will also lead to a shift in the composition of capital in the capital services index, since the user cost share of buildings will be lower. There will also, *ceteris paribus*, be a decrease in capital income, and thus a reduction in the weight given to capital in the production function. All of these effects would decrease measured inputs, just as a capital utilisation adjustment would.

We sidestep this debate, and consider options to adjust for capital utilisation, on the assumptions that one does wish to. We discuss options for implementation in Section 6.

3. Conceptual framework and approach

In this section we outline the growth accounting framework and how a capital utilisation adjustment enters, the problems with the standard hours-based approach (e.g. Basu et al., 2006), and our modification to the method which we believe overcomes these shortcomings.

3.1. The growth accounting framework

In the growth accounting framework, used by many NSIs and other researchers to measure productivity, capital and labour are the measured inputs. Changes in output that deviate from changes in the measured inputs (labour and capital) are taken to be changes in productivity.

The production function can be thought of in the following terms:

$$Y = f(L(l_1, l_2, \dots, l_n), K(k_1, k_2, \dots, k_n), \dots, A) \tag{1}$$

Where L is an aggregator function for types of labour l, and K is an aggregated function for types of capital k, and Z is an index of technology. A simple L function treats all hours worked as equivalent, so is simply a summation. A more complex L function[8] considers types of labour l that differ by age, sex, education and/or industry, with aggregation by their shares of total labour renumeration.

Following standard practice and international guidance (e.g. OECD, 2001), it is common to use a Cobb-Douglas production function, such that output Y is expressed as a function of capital K and labour L weighted together as shown:

$$Y = AL^{\alpha}K^{1-\alpha} \tag{2}$$

Where A is a measure of multifactor productivity (MFP). Taking logs on equation (1), as we are usually interested in changes over time, and let Δ denote 'change in', then the change in output is given by:

$$\Delta Y = \Delta A + \alpha \Delta L + (1-\alpha)\Delta K \tag{3}$$

It is again standard to use the labour share of income that predominate[9] in the economy (or in each industry) for α, and assuming constant returns to scale, the capital share is $1-\alpha$. Labour income is compensation of employees (wages and salaries plus other non-wage labour remuneration) and the labour share of mixed income[10], and capital income is gross operating surplus (loosely speaking: profits) and the capital share of mixed income.

The capital aggregator function K is in most cases a measure of capital services, which is a weighted index of the growth of the capital stock, where the weights are given not by their shares of the value of the stock, but by user cost shares. This has the effect of giving a greater weight to assets which are used more intensively in production, and therefore wear out quicker (depreciate quicker). The asset classes are the types of capital k.

The capital services measure can be constructed as an index, which is preferably a Törnqvist index, using two-period rolling average user cost shares, to weight the growth of the productive stock. The capital services index can thus be given as:

$$\Delta K_{i,t} = \prod \left(\frac{PS_{i,a,t}}{PS_{i,a,t-1}} \right)^{\overline{UCS}_{i,a,t}} - 1 \tag{4}$$

Where $\overline{UCS}_{i,a,t}$ is the two-period average user cost share measure in industry i, for asset a, at time t; and $UCS_{i,a,t} = \frac{UC_{i,a,t}}{\sum_a UC_{i,a,t}}$, i.e. the user cost share of asset a in industry i at time t is

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[8] The functional form of the labour aggregator function is not central to the argument, so we omit it for brevity.

[9] As a rule of thumb, the labour share is usually around two-thirds, and the capital share is therefore around one third, assuming constant returns to scale.

[10] Mixed income (the income of the self-employed, which is effectively both labour and capital income) can be divided between capital and labour income in a number of ways. One approach, used by the ONS, is to divide it into labour and capital income using the shares calculated from the corporate part of the industry.

the user cost of asset a in industry i at time t, divided by the total user cost amongst all assets in industry i at time t.

The quality of the capital services measure is inherently linked to the quality of the capital stocks measure. Capital stocks are usually calculated using the Perpetual Inventory Method (PIM) whereby a time series of investment data is cumulated, retired and depreciated[11]. The key inputs are long time series of current price capital investment data (with breakdowns by industry and asset), suitable deflators, and a set of parameters that determine the rate of retirement and depreciation of the capital stock over time. The retirement and depreciation rates are often expressed through asset life lengths, which can (but rarely do in practice) vary over time due to the composition of the broad asset class, and changes in the characteristics of the assets.

The user costs are approximated by the rental prices of the assets. Rental prices are rarely observed, as many assets have thin or non-existent rental markets. Instead, it is typical to estimate the rental price following Hall and Jorgenson (1967), which can be summarised as:

$$UC = PS \times (RoR + d - (1 + d)p) \tag{5}$$

Where PS is the value of the productive capital stock, RoR is the rate of return on capital, d is the depreciation rate, and p is the price change of a new asset (i.e. the price change for reasons other than deprecation). The productive stock is the value of the stock of the given asset, in the given industry, and the given point in time. The depreciation rate is usually the one used to calculate the productive stock, and is often specific to the asset, industry and time period. The price changes are often taken as the change in the deflator for the asset.

The rate of return can be found endogenously, if user costs are set to exhaust a known total for capital income. This is common practice in NSIs, to ensure consistency within the framework. It can also be given exogenously, often based on market rates. On the assumption of market equilibrium and thus no arbitrage opportunities, the rate of return does not usually vary by asset, but can vary by industry.

When assets are under-utilised, demand for the assets should fall, and thus we expect the rental price to fall. In the Hall and Jorgensen (1967) framework, the fall in the rental price could come from any of the components of the user cost equation, although measuring any of these in real time is challenging or impossible. We explore the three components in turn.

1. If an asset is under-utilised this might be because the rate of return on the asset has fallen. For instance, during the coronavirus pandemic, the rate of return on buildings likely fell due to increased homeworking, government-imposed restrictions and changed consumer preferences. Assuming market equilibrium, demand for other assets would respond and the average rate of return across assets stabilise at some lower level. With exogenous rates of return, this may be measured if the necessary data display the expected trends, although exogenous rates of return are often held constant in practice. With endogenous rates of return, this will depend on the response of all the other components, notably measures of capital income.

2. Under-utilisation of an asset might change its rate of depreciation, if use and deterioration are linked. National Accounts measures of depreciation are due to both

[11] Changes to the stock not accounted for by investment, retirement or depreciation should also be accounted for. These 'other changes' can include reclassification of units across industries, or reclassification of assets between classes, appearance or disappearance of assets due to discovery or accounting conventions, destruction of assets from unforeseen events such as war or natural disaster, or the premature scrapping of assets.

physical wear and tear and “normal” (foreseen) obsolescence (Eurostat, 2010). Decreased asset use might slow physical wear and tear, and thus decrease the depreciation rate. Following the user cost framework, this would reduce the rental price on the asset. However, rates of depreciation (often estimated using assumed ‘asset lives’) are usually held constant over long periods of time in standard measurement. NSIs rarely have high-frequency surveys that collect data on asset lives or depreciation rates, so any impact of changes in utilisation on deprecation rates is likely to be missed. We return to this in Section 3.4.

3. Under-utilised assets might see slower price increases or price decreases, as a result of weaker demand. Price changes of new assets are more readily measured as the change in the asset price deflator, and this usually relies on real time data collected by NSIs. This, as well as a fall in the rate of depreciation, would increase the final term of the user cost equation (since it has a negative sign), and thus move in the opposite direction to the other terms.

The net effect is *a priori* ambiguous, but it seems likely that the user cost *should* fall for under-utilised assets. However, in practice the opposite might be true. The fall in depreciation is likely to be missed given the widespread use of constant depreciation rates. An exogenous rate of return might be held constant, and an endogenous rate of return would simply respond to exhaust capital income, which might not fall, dependent on a range of other data collections for the National Accounts – so the measured rate of return is unclear. The fall in prices is most likely to recorded in real time, and would act to increase the user cost. Thus, the measured user cost may actually move in the opposite direction to what it should, at least in the short run.

Optimal growth accounting measures which have real time data on all of these components might well reflect changes in capital utilisation correctly, but in practice this will not be the case. As such, we proceed to think about implementing a capital utilisation adjustment in the context of current measurement.

3.2. Introducing a capital utilisation adjustment into the capital services measure

We modify the capital services measure K to account for utilisation by including a multiplicative factor U for each industry and/or asset:

$$\Delta\widetilde{K}_{i,t} = \prod\left(\frac{PS_{i,a,t}}{PS_{i,a,t-1}} \times \Delta U_{i,t}\right)^{\overline{UCS}_{i,a,t}} - 1 \tag{6}$$

Where terms are as previously, and $\Delta U_{i,t}$ is the (change in the) capital utilisation measure in industry i at time t.

As previously discussed, the introduction of the capital utilisation term U is unnecessary if the user costs are measured using real time data and reflect changes in capital utilisation. However, in practice, this is rarely if ever true. As such, we view this approach as a reasonable alternative. We continue to use user cost shares here, since we still want the index to reflect a relatively higher weight for shorter lived assets. The capital utilisation term U thus attempts to embody the changes in the user costs that should take place from a change in utilisation, but do not as a result of imperfect measurement.

If U is the same in every period, then this drops out in the construction of the capital services index, and has no effect on productivity. That is, with constant U for all assets, equation (6) collapses to (4).

To implement, we construct a Törnqvist index, using two-period rolling average user cost shares, to weight the growth of asset utilisation measures within each industry:

$$\Delta U_{i,t} = \prod \left(\Delta U_{i,a,t}\right)^{\overline{UCS}_{i,a,t}} - 1 \tag{7}$$

Recall that for some assets we assume constant utilisation, that is $\Delta U_{i,a,t} = 0$.

This is consistent with equation (6), as we estimate the unadjusted capital services measure first, and apply the utilisation adjustment onto that. We use user cost shares here again for consistency with the unadjusted capital utilisation measure in (5), reflecting the relative importance of each asset in the capital services measure. This gives an aggregate capital utilisation index for each industry. Substituting (7) into (6) and evaluating, gives:

$$\Delta \widetilde{K}_{i,t} = \left(1 + \Delta K_{i,t}\right) \times \left(1 + \Delta U_{i,t}\right) - 1 \tag{8}$$

In words, the growth in the utilisation-adjusted capital services index in industry i is (1 plus) the growth in the unadjusted capital services series in industry i, multiplied by (1 plus) the growth in the utilisation series in industry i (minus 1). This gives an intuitive interpretation: the utilisation-adjusted capital services index is approximately[12] the change in the unadjusted capital services index, plus the change in the capital utilisation index, and thus changes in the utilisation-adjusted index can be approximately decomposed into changes in 'potential capital services' (i.e. unadjusted capital services) and changes in utilisation.

The addition of a utilisation index in this way is similar to the method employed by Fernald (2014), but the aggregation by asset is, we believe, unique to this paper, since other methods typically make use of a single utilisation measure covering all assets within an industry or economy.

3.3. The problem with the standard hours-based approach

While an hours-based approach to capital utilisation adjustment is most promising and most widely recognised, it suffers from several conceptual drawbacks.

First, the utilisation series is based on hours worked of all workers. This assumes that all workers use capital in proportion to their hours worked – that is, people who work more hours use more capital, but everyone who works any hours uses some capital. Clearly this is untrue – some people use capital to a far greater extent than others. Contrast a machine operative in a manufacturing firm with a worker in the finance department of the same firm: the machine operative will clearly use much more capital than the finance worker, but their hours are treated equivalently in the standard approach.

Relatedly, the method assumes that reductions in hours worked by some staff can be offset by increases in hours worked of other staff for the same capital. In some way, this implies interchangeable skills in the workplace. Consider a two-worker firm, where one uses capital (call her the woodworker) and one does not (call her the manager). Assume both work equal hours in the first period, but the woodworker drops their hours by half in the second period –

[12] Ignoring the interaction term, since unadjusted capital services changes are small, and utilisation changes are usually also small, so the interaction term is approximately zero.

the capital utilisation rate would only fall by a quarter, although the person using the capital drops their hours by half. If the manager increased their hours by an equivalent amount in the second period, then average hours (and therefore the standard hours-based capital utilisation adjustment) would be the same as in the first period, but if the manager does not use capital this should be irrelevant to the capital utilisation rate.

The standard method also assumes that all types of capital are affected equally. That is, for any change in hours worked, utilisation of all types of capital change equivalently. Returning to our previous two-worker firm, this time let us distinguish between two types of capital (call them machines and computers), and let us assume the woodworker uses machines, and the manager uses computers. If the woodworker drops their hours, the standard hours-adjustment would reduce utilisation of both machines and computers. Again, this is a shortcoming of the method.

Most obviously, the standard model assumes that hours worked and capital utilisation move in tandem to the same degree. The coronavirus pandemic makes it evident that this is not true – homeworkers can work as many hours as before the pandemic, but without using as much of their business' capital (e.g. they do not need to use the business' building). Similarly, any capital that operates without human intervention fails this assumption – such as automated machines and software, and copyright assets (that produce income based on consumer behaviour, not that of the asset owner).

Finally, the standard application of the hours-based method will typically result in falling utilisation of assets over time in a deterministic way, as average hours worked have fallen in most developed countries in recent decades. Through increases in standards of living, improved labour market regulation, and the introduction of newer assets which require less labour to work effectively[13], average hours worked have been on a steady downward trend for years. When changes in average hours worked are used as the measure of capital utilisation, this therefore also implies that capital utilisation is slowly falling over time, which is a challenging view. We see these trends as structural changes, rather than variations in capital utilisation.

In sum, the standard hours method assumes all workers use all types of capital equally (proportionately to their user cost shares), and any changes in hours of any worker affect all types of capital equally. This method is probably best suited to traditional manufacturing industries, where workers operate machines one-to-one, and there was a clear relationship between the hours of the worker and those of the asset. For most of the modern economy, however, this is likely to be a poor proxy.

To improve on the standard method, and overcome many of the shortcomings described above, we propose two innovative modifications: using the hours of only certain occupations for certain assets; and adjusting utilisation of different assets to different degrees.

3.4. Occupation-asset matching

First, we consider only the hours worked of occupations that would be expected to use given assets. In the case of general use assets such as buildings, we take the hours worked of the whole industry. For specific assets such as transport equipment or machinery, we select only a subset of occupations. This overcomes the issue described above, whereby all workers

[13] For instance, older aircraft needed three or four pilots, and now they all use two because they are better machines which can do much more of the work themselves. You would not want to take this introduction of more efficient equipment to mean that the asset was underutilised. Thanks to Joe Murphy for this insight.

are assumed to use all capital equally – now, only the hours of relevant occupations will be considered, and the hours worked of other occupations have no effect on the utilisation of that type of asset. The average hours worked of a factory floor worker will be far more representative of the utilisation of a machine than the average hours worked of a desk-based worker in the same industry. This also overcomes an issue associated with homeworkers, especially relevant during the pandemic, since workers that can work from home are likely not those that will be needed to use assets *in situ*.

Table 1 – Assets and associated occupations

Asset	**Occupations**	**Comments**
Other buildings	All (non-homeworking hours)	All workers in business owned buildings, hence non-homeworking hours only
Structures	All	This class includes roads and a range of public infrastructure, used indirectly by most workers
"Heavy" other machinery and equipment (OME)	A range that use agricultural, manufacturing, construction or other substantial machinery or equipment	See text for more details
"Light" other machinery and equipment (OME)	All	"Light" OME encompasses office furniture, shelving, etc. and it is difficult to think of any occupations that use none of these types of capital
IT hardware and telecoms equipment	Primarily office-based occupations, and other occupations that use ICT equipment	
Transport equipment	Drivers, pilots, etc. and all occupations where transport equipment is integral to their role, including flight attendants and car mechanics	Heavily concentrated in certain industries
Cultivated assets	N/A	No variation
Software and databases	As for IT hardware and telecoms equipment	
Entertainment, literary and artistic originals	N/A	No variation
Research and development	N/A	No variation
Mineral exploration and evaluation	All	Only present in the mining and quarrying industry, where utilisation of the asset reflects the degree of activity and hence is well proxied by all hours worked

Notes: Since MFP estimates produced by the ONS are for the market sector only, Table 1 excludes weapons systems, transfer costs, and dwellings assets. A full list of occupation codes matched to the three assets with most distinct definitions (ICT equipment and software, "heavy" OME, and transport equipment) is in Annex 2.

A summary of the occupations matched to the assets in this method are given in Table 1. Some assets have broad use, and therefore we use hours worked across the whole industry (all workers are assumed to 'use' buildings to the same degree when present). Strictly, this should be office-based hours, which we estimate based on workers' reported homeworking activities, but these follow a similar pattern to all hours worked (aside from the pandemic period). Utilisation of ICT, telecoms equipment, and software and databases, are proxied using desk-based occupations; and utilisation of transport equipment proxied by transport related occupations (drivers, etc.). Utilisation of most intangible assets and cultivated assets are assumed not to vary (see Section 3.4) so do not have occupations matched.

The most challenging asset class is 'other machinery and equipment' (OME) which accounts for a very heterogenous set of assets, including manufacturing machinery, medical equipment, industrial cleaning equipment, mining and agricultural machinery and equipment, lighting, office furniture, and more besides. To tackle this broad range, we split the class in two:

- "heavy OME", encompassing all substantial, valuable, long-lasting and highly productive assets, including manufacturing machinery, medical equipment, industrial cleaning equipment, mining and agricultural machinery and equipment

- "light OME", everything else in the asset group, including lighting, office furniture, shelving and storage equipment, etc.

In many services industries, "light OME" accounts for 90% or more of the OME capital stock (ONS, 2019). Given the broad nature and use of many of these assets, it is difficult to think of a single occupation that would not use at least some "light OME". As such, we assign occupations to the "heavy OME", but use the hours worked of all workers for "light OME". We combine these categories according to the share of the "heavy OME" occupations in total hours worked in the industry, giving these occupations twice their normal weight, since the asset life of "heavy OME" assets is usually at least twice that of "light OME" (ONS, 2019).

3.5. Variations by asset

To account for the different degrees to which utilisation can fall for different assets, we appeal to the concept of depreciation. As argued in Section 3.1, our capital utilisation measure is trying to compensate for the lack of adjustment in the user cost equation from using imperfect data. One of the factors that should be adjusting is the rate of depreciation.

In many cases, the depreciation of the asset is intrinsically linked to its use. Repeated use of a machine or vehicle contributes to its deterioration through wear and tear. However, depreciation is not due only to physical wear and tear; it is due also to "normal" (foreseen) obsolescence (Eurostat, 2010). The degree to which depreciation rates (and asset life lengths) reflect these two factors differs dramatically by asset class. Intangible assets, for instance, do not physically deteriorate at all – the entirety of the depreciation is therefore due to obsolescence. On the other hand, manufacturing machinery and vehicles are known to wear out long before they cease to be useful, as evidenced by thriving second-hand markets.

The balance between use-based depreciation (physical wear and tear) and time-based depreciation (obsolescence) is a good match for the argument in Section 3.2, that some assets can vary in utilisation more than others. Since depreciation does not depend entirely on use, neither should our utilisation measures. Put another way, even with perfect data, the rate of depreciation in the user cost equation would not fall to zero even with zero use of the asset, due to continued obsolescence.

In addition, some assets continue to provide capital services even when not actively used. For instance, buildings continue to offer capital services in the form of shelter and storage for other capital assets and inventories, and perhaps even some services in the form of branding for the firm, even when not used by workers; in other words, buildings are always used to some extent. Some machines, and especially intangible assets, are automated, and therefore function without the need for labour hours. Other types of equipment continue to offer services in the form of storage and protection for assets, even when not actively managed. The meaning of 'use' is somewhat unclear in the case of cultivated assets (such as dairy cattle and orchards), which will continue growing and developing over time regardless.

In the case of intangible assets, they do not physically deteriorate at all, and all deprecation is due to obsolescence by definition. Some software and databases are 'used' by workers, although many are automated and most could be used by homeworkers, so hours worked are probably a poor proxy for utilisation in this case. Similarly, mineral exploration and evaluation assets are 'used' by mining and quarrying firms to inform operations, and reduced mining operations would preserve the value of the information asset for longer; however, such considerations are generally made over the medium term, and as such changes in hours in the short run are somewhat disconnected from the asset.

More broadly, if there is any obsolescence, which is surely true for all assets to a greater or lesser extent, then there will be some depreciation and therefore some 'user cost' at all times – as such, some capital services must be delivered. Utilisation adjustments of less than 100% therefore seem appropriate in all cases.

The true extent of the role of each factor in depreciation of each asset is unknown, but we postulate a sensible set of factors that account for the heterogeneity of assets. Table 2 provides a summary. We believe it should be possible to estimate at least some of these factors through analysis of data in second-hand markets (especially for cars, for instance), although this is beyond the scope of the present paper.

Table 2 – Assumed use-based deterioration factors by asset

Asset	**Typical depreciation rate**	**Assumed use-based deterioration factor**	**Rationale**
Other buildings	c. 5%	20%	Depreciation mainly due to obsolescence and weathering over time. Continues to provide services in the form of shelter/storage even when not used. Use may even reduce deterioration.
Structures	2-5%	50%	Clearly some depreciation of roads and other public infrastructure through repeated use but given long asset lives, much of the depreciation is also due to obsolescence and weathering over time.
Transport equipment	15-20%	80%	Mostly due to use, since many mechanical parts that wear out through

			repeated use, e.g. miles on a car. As with all assets, some obsolescence and weathering over time. May be possible to estimate through analysis of second hard markets for cars.
Other machinery and equipment	10-15%	80%	Mostly due to use, since many mechanical parts that wear out through repeated use. As with all assets, some obsolescence and weathering over time.
Telecoms equipment	c. 20%	20%	Have relatively short asset lives, mostly due to high rates obsolescence due to technological change. Use largely due to consumers rather than producers, and many assets will be automated.
IT hardware	c. 40%	20%	Have relatively short asset lives, mostly due to high rates obsolescence due to technological change. Strain on processors from use can lead to failure of components, although more likely due to time. Assets can be fragile.
Cultivated assets	c. 40%	0%	Meaning of ‘use’ in this case is somewhat unclear, but assets will continue growing and developing over time regardless of harvesting. Effective management and use (harvesting) may even reduce deterioration.
Software and databases	c. 40%	20%	As an intangible, no physical wear and tear is possible, but the rate of obsolescence could be linked to use – since reduced use might delay the extraction of value from database assets. Utilisation could also vary, as some software and database assets will be actively used by workers.
Mineral exploration and evaluation	c. 20%	20%	As an intangible, no physical wear and tear is possible, but the rate of obsolescence could be linked to use – since reduced use might delay the extraction of value from the information assets.
Entertainment, literary and artistic originals	c. 20%	0%	Depreciation based solely on obsolescence over time, linked to royalties from, and sales of, licenses to use and copies of the asset. Driven by demand and consumers, rather than owners.
Research and development	20-30%	0%	Depreciation based solely on obsolescence over time, linked to product cycles of relevant products. Driven by demand and consumers, rather than owners.

Notes: Since MFP estimates produced by the ONS are for the market sector only, Table 2 excludes weapons systems, transfer costs, and dwellings assets. Depreciation rates given are typical, but vary by industry in ONS capital stocks and capital services measures.

3.6. Bringing it all together

From Section 3.4 and 3.5 we have argued that:

- Only certain occupations use certain assets, and therefore the hours of those workers alone are suitable to adjust for the utilisation of those assets; and
- Only certain assets are subject to variations in utilisation, and to different degrees, and should continue to depreciate due to the passage of time to a greater or lesser extent, regardless of use.

This framework provides a novel way to apply a capital utilisation adjustment.

Our asset utilisation measures are constructed by:

$$\Delta U_{i,a,t} = \left(\frac{r_{i,a,t}}{r_{i,a,t-1}} - 1\right) \times F_a \quad (8)$$

Where $r_{i,a,t}$ is the ratio of actual hours worked in the relevant occupation group for asset a, in industry i, at time t; and F_a is the use-based deterioration factor (as described in Section 3.5) for asset a (these do not vary over time of by industry by assumption). Recall that for some assets we assume constant utilisation, that is $r_{i,a,t} \equiv r_{i,a,t-1}$.

Then the industry utilisation measure is constructed as in equation (7), restated below:

$$\Delta U_{i,t} = \prod \left(\Delta U_{i,a,t}\right)^{\overline{USC}_{i,a,t}} - 1$$

While this still rests on the estimation of the degree of change in asset use (embodied in r), it does so to a lesser extent, and in a more appropriate way. As such, it overcomes, to some extent, the shortcomings of the method described in Section 3.3, namely that hours worked and capital utilisation move in tandem to the same degree. It does this by applying these adjustments only to assets which have such a link between workers and utilisation. Using the hours worked of particular occupations, as outlined in Section 3.4, further improves the method by ensuring the hours worked measures are as appropriate as possible for that asset, overcoming the other shortcomings described in Section 3.3.

4. Data and methods

In this section we discuss the methods and data used to estimate the series described in Section 3.4, namely the assignment of occupations to assets, and the estimation of hours worked of these groups (including office-hours worked).

4.1. Assignment of occupations to assets

We used three main resources to assign occupations from the Standard Occupation Classification (SOC) 2010 to the asset classes used in ONS capital stocks and capital services measures.

First, we used the descriptions of assets given in the European System of Accounts (ESA) 2010 (Eurostat, 2010) and the System of National Accounts (SNA) 2008 (United Nations *et al.*, 2009) to gain a detailed understanding of the nature of the assets. Where relevant, we drew also on other materials, including the OECD Measuring Capital Manual (OECD, 2009), and the Classification of Products by Activity (CPA) revision 2.1, especially in the case of other machinery and equipment, which is a diverse group. Recall from Table 1 that we are selecting occupations only for three assets: “heavy” OME (see Section 3.3 for the meaning of this), transport equipment, and ICT hardware (also used for software).

Second, we used resources available from the ONS website to explore each of the 369 4-digit SOC 2010 codes, to gain an understanding of the tasks performed by workers in these occupation groups. This allowed us to make an informed assignment of each occupation code to be a user of one or more of the relevant assets.

Finally, we used data from the US O*NET database on the nature of jobs of different occupations to quality assure our assignments. O*NET collects a huge amount of valuable data on the tasks of different occupations, based on detailed interviews with workers in the US economy (see National Center for O*NET Development, no date). While the nature of some roles may differ between the UK and the US, this is nonetheless a useful resource.

The relevant variables from O*NET are the mean score to the questions given below. In each case, respondents report how important the task is (on a 5-point scale), and the ‘level’ of the task (on a 7-point scale). A higher level means that the task is more demanding, and in our case can be interpreted as using the asset more intensively, or using a higher value asset. In each case, examples are given for points 2 (low), 4 (medium) and 6 (high) of the 7-point ‘level’ scale, and are listed below.

- “Heavy” OME - Controlling Machines and Processes: “Using either control mechanisms or direct physical activity to operate machines or processes (not including computers or vehicles).”
  - Low – Operate a cash register
  - Medium – Operate a drilling rig
  - High – Operate a precision milling machine

- ICT equipment – Interacting With Computers: “Using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information.”
  - Low – Enter employee information into a computer database
  - Medium – Write software for keeping track of parts in inventory
  - High – Set up a new computer system for a large multinational company

- Transport equipment – Operating Vehicles, Mechanized Devices, or Equipment: “Running, maneuvering, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or water craft.”
  - Low – Drive a car
  - Medium – Drive an 18-wheel tractor-trailer
  - High – Hover a helicopter in strong wind

The matches to the asset classes are good, and the tasks and assets described for the level are all consistent with the assets in question.

The O*NET data were matched[14] from US to UK occupation codes, via the international standard occupation codes (ISCO08), using a series of publicly available conversion

[14] Given the multi-match nature of the conversion, we took a simple arithmetic average across all converted scores to arrive at one combined score per UK SOC code.

tables[15]. For each question (asset), we multiplied the level (intensity) by the importance to give a composite score.

While these scores give a useful indication of relative ranking and importance by occupation, it is not clear where the line should be drawn – i.e. above what composite score should an occupation be flagged as 'using an asset'. In truth, it is likely a grey line. We therefore used the O*NET data in conjunction with our own research (outlined above) to assure and inform our allocation, but did allow deviation from the rankings implied by the O*NET data. Table 1 gives a summary of the types of occupations included for each asset, and the full list of allocations in in Annex 2.

4.2. Estimation of hours worked

We estimate hours actually worked of these asset-occupation groups at quarterly frequency using data from the Labour Force Survey (LFS). To do this, we aggregate all hours worked of occupations within an asset group, by industry, using the total hours actually worked variable (ttachr). To generate a long time-series, this requires converting the industry (SIC) and occupation (SOC) classifications at the relevant points, which we do using standard modal mappings at the most detailed level available.

We also compute total usual hours worked of each group in the same way. This allows us to estimate a utilisation level in an intuitive way: hours actually worked divided by hours usually worked. Absences from work for any reason (sickness, holiday, strikes, enforced closure or lockdown, etc.) should appear as a deviation of the actual from the usual, and therefore a reduction in the utilisation rate. Conversely, an increase in hours relative to the usual (due to overtime, or a reduction of the aforementioned absences) would increase the utilisation rate.

To estimate homeworking hours (since we measure the utilisation of buildings as the inverse of homeworking hours), we use variables on homeworking behaviours collected on the LFS, although some variables are collected only from Wave 1 respondents, and are therefore available only in the Annual Population Survey (APS) dataset.

Following ONS (2021a), we define 4 homeworking statuses, based on 3 homeworking questions:

- Mainly work away from the office – respond that the place they 'mainly work' is *not* "separate to their home" [e.g. an office]

- Recently worked from home – respond that the place they mainly work is "separate to their home", but that within the last week they worked at least some time "in their own home"

- Occasionally work at home – respond that they mainly work "separate to their home", and within the last week they did not work "in their own home", but respond that they do "ever" [sometimes] work from home

- Never work at home – the remainder after the above have been assigned

We then assign a fraction of each person's time to be homeworking hours, depending on their homeworking status, as shown in Table 3. These are informed by estimates from the

[15] Available from the Reference and Management of Nomeclatures (RAMON) from Eurostat, available: ec.europa.eu/eurostat/ramon.

Understanding Society survey (see Felstead and Reuschke, 2020), which ask for more detail on the intensity of homeworking. Our buildings utilisation measure is based on all hours worked that are not estimated as homeworking hours.

Table 3 – Homeworking hours

Homeworking status	Proportion of hours assumed to be worked at home	Comments
Mainly work at home	90%	Equivalent to one day a week in the office every other week, on average
Recently[16] worked from home	25%	Equivalent to one day a week at home for most, and some for a little longer, on average
Occasionally work at home	5%	Equivalent to one day at home a month, on average
Never work at home	0%	

Prior to 2008, we do not have access to the data on 'recently' or 'occasionally' homeworking, so we extend the series using the trend in the mainly homeworking group by industry, which follows a similar trend in the years after 2008 (except in 2020, for obvious reasons).

4.3. Adjusting the baseline

It is important to de-trend actual hours worked in some way, else changes over time may be due to changes in technology or productivity that lead to fewer hours being worked per person in some industries. Usual hours worked is an attractive baseline, since it relates specifically to workers and their perceptions of "usual" – allowing for changes in contracts, working arrangements and behaviours over time. It is available at the same frequency and granularity as the actual hours worked variable, and is simple to implement.

However, using usual hours worked from the contemporaneous period, without adjustment, as the baseline proved to be problematic. Not only was it somewhat volatile, but it responded 'too quickly' to shocks such as the 2008/09 financial crisis. When workers were laid off, their actual and usual hours fall to zero, and hence the impact on the ratio for the industry was essentially nil. We wanted such a scenario to generate a temporary fall in utilisation, until the business could adapt by selling/scrapping their capital and/or hiring workers to use existing capital again.

We tested a number of adjustments:

1. Use usual hours worked, but smooth it with a high filter (within each industry and asset class). Depending on the specifications and parameters, this would create a smoother and more-slowly-adjusting baseline, and hence a temporary fall in utilisation when actual hours falls. However, this adds choices and processing steps to an already complicated process, and could lead history to be revised with every

[16] There is an interesting question on reporting behaviours – whether people considered themselves to 'mainly' work from home during the pandemic, or whether they still 'mainly' work away from home, but worked at home during the week before the interview. If the latter, we may need to adjust the proportions in Table 3 over time. This is difficult to know for sure, and we do not make an adjustment here.

update due to the nature of filters like these. Kurmann and Sims (2021) document large revisions in the utilisation-adjusted TFP measures produced by John Fernald in the US (e.g. Fernald, 2014) who uses this 'de-trending' approach. We look to avoid this issue[17].

2. Detrend hours actually worked, and use variations around the trend (with no role for usual hours worked) – this would have a similar effect to (1), with the series now based around 1 rather than 0.8-0.9 (although we view our method as unable to produce an estimate of the 'level' of capital utilisation). It has the same drawbacks as (1), with additional steps and decisions to be taken and potential for frequent revision to the backseries.

3. Account for the hours worked of people no longer in the industry in the base line – for instance, those made redundant. Assuming firms take x periods to respond to loss of labour by re-hiring workers or selling capital, in the short run, the hours worked of previously employed workers could be included in the baseline. This would require rolling forward the hours usually worked by people who have left jobs (for a variety of reasons) for x quarters. This would not be susceptible to future revisions, although does require some careful data processing and some assumptions to be made on the hours worked of those no longer working.

4. Apply a simpler 'smoothing' approach to usual hours than (1), such as taking a four-quarter (backward looking) rolling average, or using a one- or two-period lag – these are also not susceptible to future revisions, and are much easier to implement. A choice must be made about how longer the lag or average should be, although some choices are intuitive.

We tested 5 adjustments: de-trending usual hours using a filter; the addition of previously-employed worker-hours; a four-quarter (backward looking) rolling average of usual hours, and, one-period and two-period lags of usual hours. We did not test option (2) above, since we quickly discounted using a filter based on the criticisms of the approach in Kurmann and Sims (2021).

Annex 1 shows the resultant capital utilisation series for each of the adjustments, for the market sector aggregate and for manufacturing. We adopted the four-quarter backward looking rolling average of usual hours as our central case. Thus, we see the business as slowly updating their expectations based on the norm over the course of the preceding year, which seems reasonable. Annex 1 also shows our central case (using the four-quarter backward looking rolling average of usual hours as the basseline) and the 'no adjustment' (using the contemporaneous usual hours worked data) for each industry section (letter-level).

5. Results

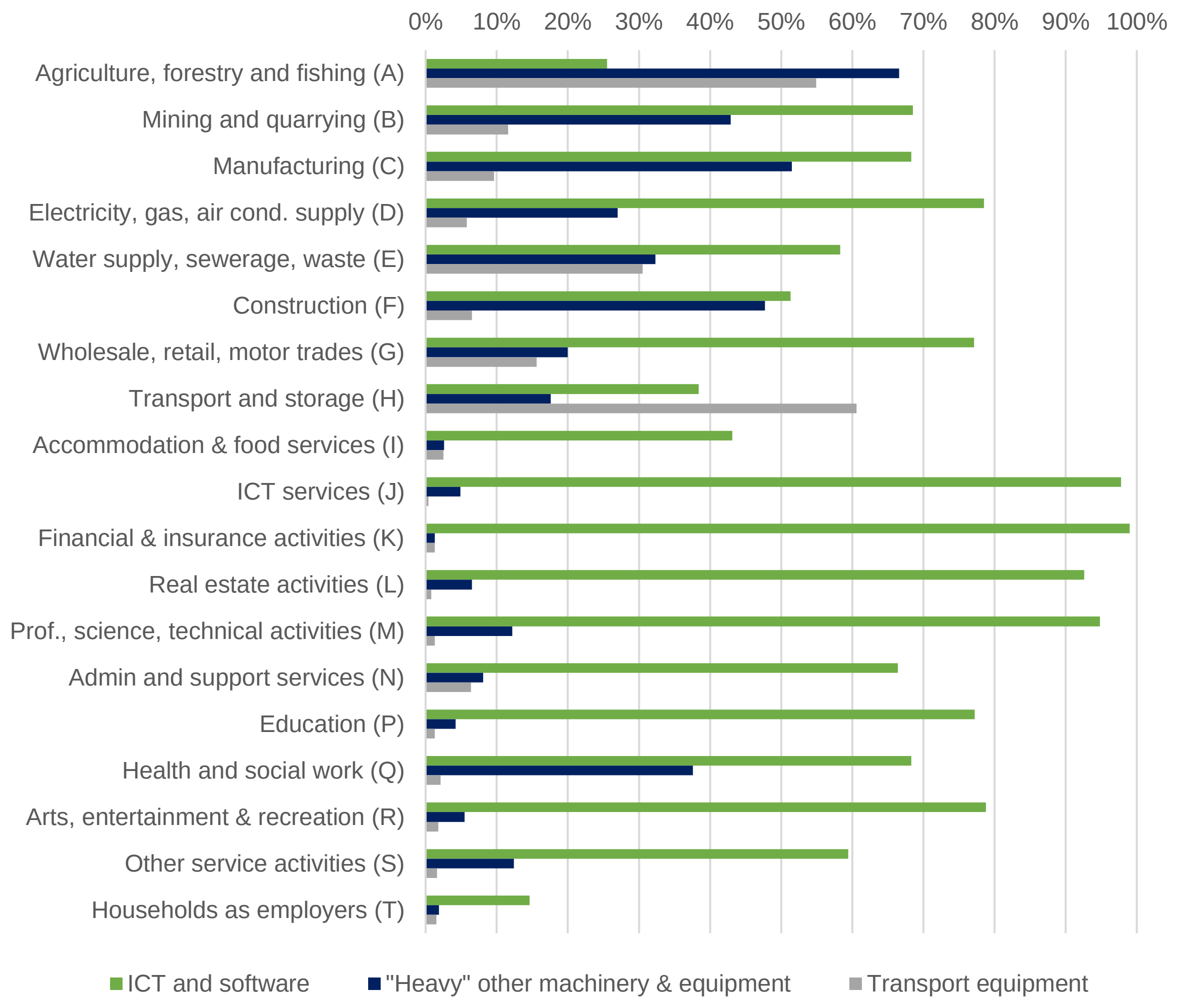
In this section we first show some results of the hours worked of the different occupation-asset groups by industry, to show that they produce sensible results with regards to their allocation. We then show the trends over time in the homeworking-hours series, and finally the utilisation series.

[17] We are grateful to Ana Galvão for this suggestion.

5.1. Hours worked of different occupation-asset groups by industry

Figure 1 shows the proportion of hours worked within our occupation-asset groups, in each section-level industry from the SIC 2007 industry classification. Since occupations can be in more than one asset group, or none at all, the bars will not add to 100% within each industry, nor across industries. Rather, the proportion represents the fraction of hours worked in that industry which our method suggests are worked by people who use the relevant asset. The data are for 2018 hours worked.

Figure 1 – Proportion of hours worked in each occupation-asset group, by industry, 2018



The proportions in Figure 1 accord with expectations – transport assets are used most in the transport industry (H), followed by agriculture (A) (which includes fishing), water and waste (E) (which includes waste collection services, e.g. bin lorries), and retail (G) (which includes the motor trades industry). Public admin (O) also has a relatively large transport share, which is likely due to the police and military in this industry.

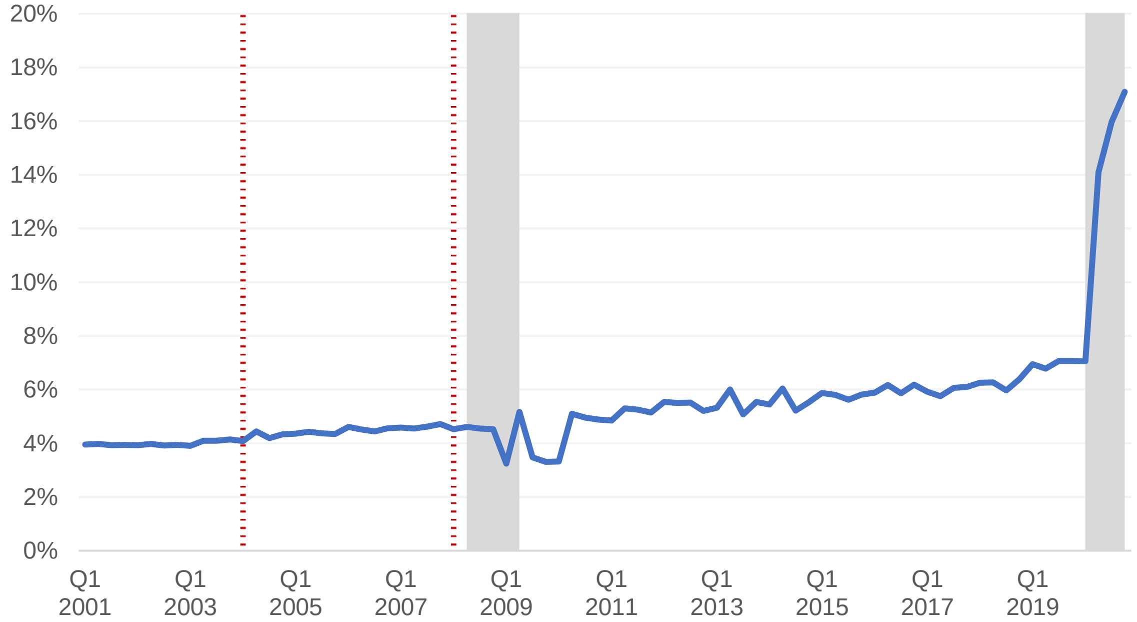
ICT assets are used widely, but most in business services industries (K, L, M) and the ICT services industry (J), unsurprisingly, and least in agriculture (A), transport (H) and accommodation and food services (I). “Heavy” OME is used most intensively in all the production industries. The healthcare industry (Q) also has a higher OME share, reflecting medical machinery and equipment. Note that the industry aggregation used in Figure 1 hides some variation at lower levels, shown in Annex 3.

5.2. Trends in homeworking hours

Although buildings make up a large fraction of the capital stock in the UK, they make up a smaller fraction of the capital services index (due to their relatively lower weighting in user costs) and a yet smaller impact on our capital utilisation measure. This is because of the use-based deterioration factor for buildings we adopt (see Table 2), where we assume that buildings are employed largely constantly over time, irrespective of whether workers attend them. In our method, only 20% of the overall utilisation of buildings is allowed to vary according to the hours worked by workers in business-owned buildings; the other 80% is assumed to be constant, as a result of buildings being employed to provide storage and shelter for other capital goods and inventories, and ongoing branding services.

Figure 2 shows the fraction of hours worked in the whole economy estimated to be worked at home, which is the inverse of our buildings utilisation measure. This rises slowly over time, from around 4% in the early 2000s, to about 6-7% in recent years. The coronavirus pandemic results in a massive increase in homeworking. The economic downturn is visible in this data, albeit with an unusual pattern – an apparent temporary decrease in the fraction of hours worked at home between 2009 Q1 and 2010 Q1, with the exception of 2009 Q2.

Figure 2 – Estimated fraction of hours worked at home in the whole economy, 2001 Q1 to 2020 Q4



Notes: Breaks in time series shown by red dotted lines: in Q1 2004, due to switch from LFS (before) to APS (after); in Q1 2008, due to switch from only "mainly" homeworking behaviour (before) to include lower-intensity homeworking behaviours (after). Recessions shown by grey shaded areas.

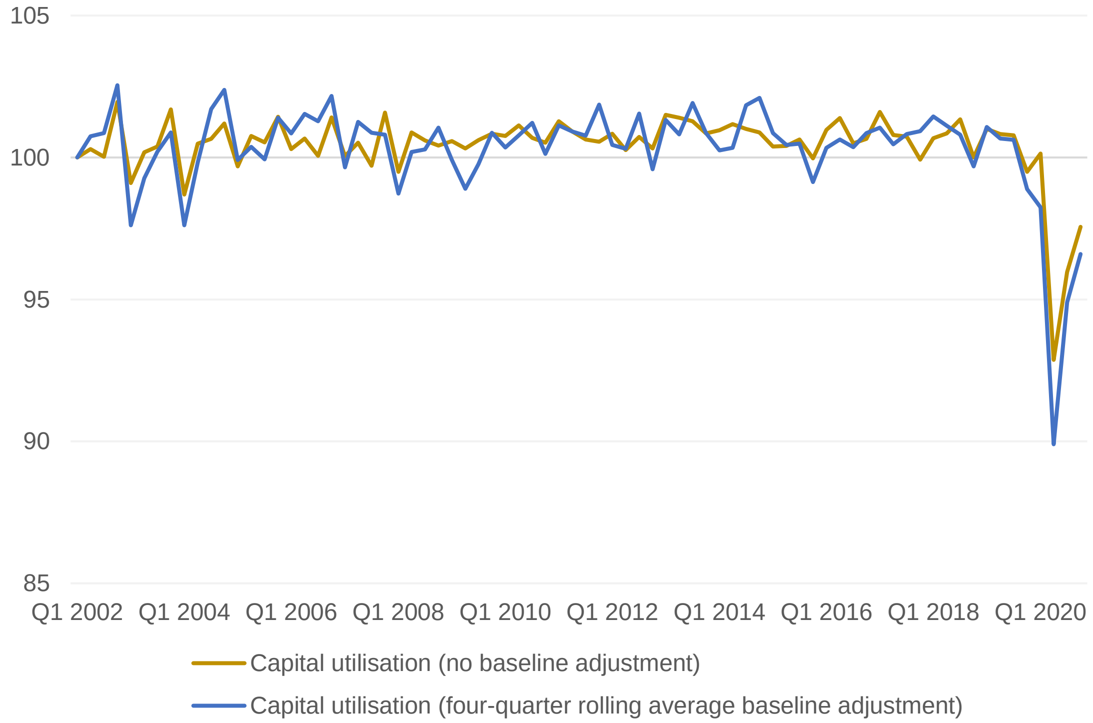
The trends by industry are as expected, with professional services and ICT industries exhibiting far higher degrees of homeworking than other industries. The creative, arts and entertainment activities industry has the highest share, at around a quarter of all hours worked in that industry done at home. The homeworking share in almost every industry is flat or increasing over time, with the exception of a few small industries. The break points and industry conversions occasionally cause increased volatility in the backseries.

5.3. Trends in asset utilisation rates for the market sector

We apply the trends in asset utilisation rates and homeworking hours with the use-based deterioration factors in Table 2 and the user cost weights in the ONS MFP (ONS, 2021b) system to derive an overall estimated capital utilisation adjustment for each industry, and the market sector as a whole (see Sections 3.1, 3.2 and 3.5 for algebra). Figure 3 shows the market capital utilisation series, indexed to 2002 = 100, with and without the four-quarter rolling-average adjustment described in Section 4.3.

Across the market sector as a whole, capital utilisation varies between about +2% and -2% in each quarter between 2001 and 2008, and between about +1% to -1% between 2008 and 2019. The reduction in volatility could be due to somewhat artificial changes in the data from this point onwards: perhaps due to the SIC conversion used for the historic data causing a break at this point. The smaller changes from 2008 onwards feel more realistic, but we have no clear evidence for preferring one period or the other.

Figure 3 – Capital utilisation, with and without the four-quarter rolling average adjustment to the baseline, UK market sector, Q1 2002 to Q4 2020, indexed to Q1 2002 = 100



Notes: Weighted by user cost shares from ONS MFP system – across assets within each industry, and across industries in the market sector. See Section 3.1, 3.2 and 3.5 for algebra.

The series is not especially cyclical – the 2008/09 economic downturn is characterised by a reduction in volatility and seasonality, but no substantial or sustained dip in utilisation. This is for two reasons: first, in many industries, there was no noticeable fall in hours worked in that period – the characteristic 'labour hoarding' phenomenon; and second, if there was a fall in actual hours worked, then usual hours worked tended to fall a similar amount, and hence the ratio between them was relatively unchanged. Our rolling-average adjustment to the baseline mitigates this somewhat, although this isn't enough to generate a significant effect at the market sector level.

The coronavirus pandemic is very visible, with a drop in utilisation of some 10% overall in Quarter 2 2020, before rebounding. This is by far the largest movement in the series, although less than some might have expected. This reflects the targeted use of occupations and the asset-use factors which subdue the effects of reduce hours worked, to account for some degree of continued asset-use at all times.

The data are not seasonally adjusted, and show some interesting seasonality, summarised in Table 4. Utilisation tends to increase in Quarters 2 and 4, and decrease in Quarters 1 and 3 – Table 4 gives some details of the seasonal patterns, including by industry. Lower utilisation in Quarter 1 could be due poor weather disrupting operations, winter illnesses, and low demand after the Christmas period; Quarter 3 overlaps the UK school summer holidays so could exhibit a larger degree of absence for holidays. Meanwhile Quarter 4 is likely to be characterised by increased operations in the run up to Christmas and other festivals; and Quarter 2 is the quarter with least disruptions for any of the above reasons. Typical seasonal industries (such as water transport and air transport) demonstrate the strongest seasonal effects, but the pattern is widespread.

Table 4 – Seasonal characteristics of the utilisation adjustments

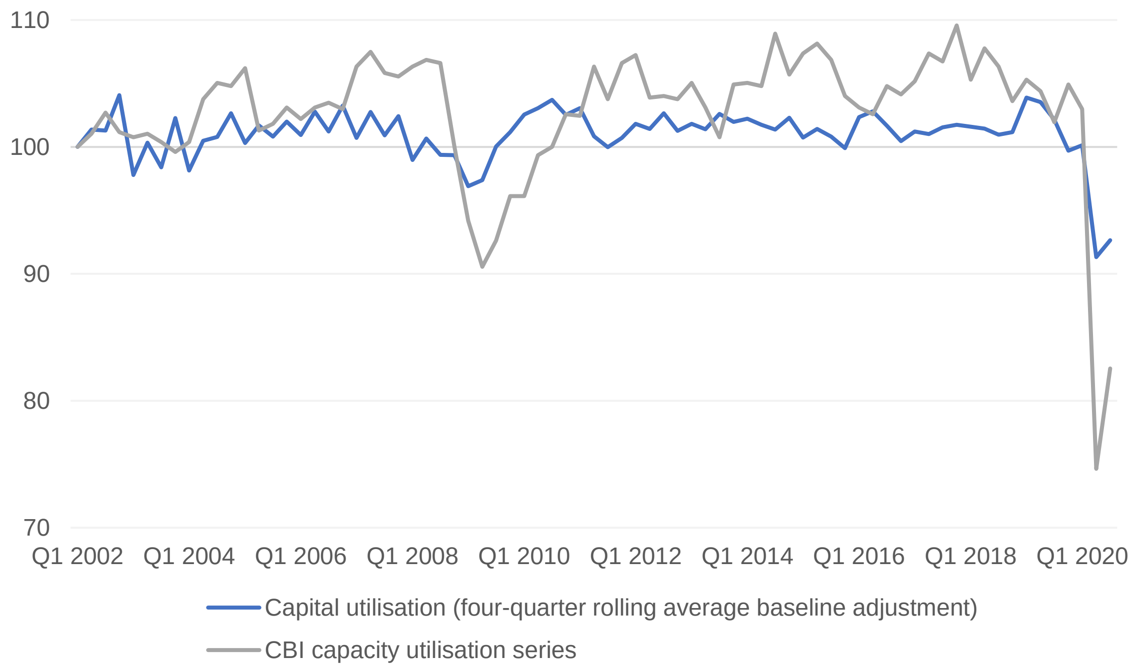
Quarter	Average quarter-on-quarter change in utilisation, whole economy	Number of industries consistent with whole economy change	Median quarter-on-quarter seasonal effect by industry	Industries with largest negative effects	Industries with largest positive effects
1 (Jan to Mar)	-0.34%	48	-0.08%	Water transport, travel agency, air transport	Repair of household goods, insurance
2 (Apr to Jun)	0.30%	48	0.20%	Water transport, insurance, water supply	Fishing, air transport, forestry
3 (Jul to Sep)	-0.13%	47	-0.20%	Education, manuf. of rubber products, repair and instal. of machinery	Air transport, fishing, manuf. of coke/petrol, water transport
4 (Oct to Dec)	0.16%	43	0.19%	Fishing, air transport, travel agency	Education, water transport, rental and leasing

Notes: Averages 2002 to 2019.

5.4. Trends at industry level

As noted in Section 2, there are other methods and sources used in the literature to measure capital utilisation. Figure 4 compares the hours-based measures constructed in this paper, for the manufacturing industry, with the data from the CBI survey on capacity utilisation (covering the manufacturing and mining industries). Besides the pandemic period, the series are essentially unalike – the CBI series is far more cyclical than the hours-based measure, including during the 2008/09 downturn. However, the CBI is strictly one of *capacity utilisation* which includes the utilisation of other factors of production like labour – this could influence the measure.

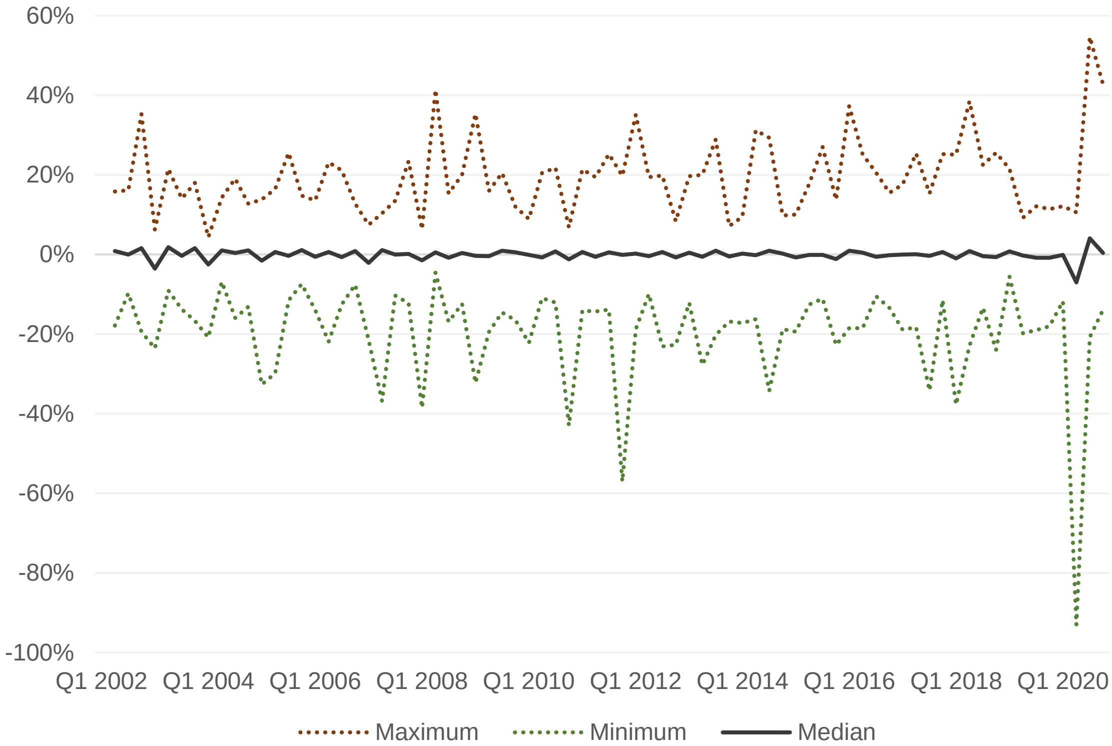
Figure 4 – Comparison of hours-based capital utilisation (manufacturing industry) and CBI utilisation (manufacturing and mining), Q1 2002 to Q3 2020, indexed to Q1 2002 = 100



Sources: this paper, Confederation of British Industry (CBI)

Figure 5 shows the median, minimum and maximum quarterly change across the 62 industries in the ONS MFP system (unweighted by size and capital intensity of industry). The median change in Q2 2020 is the largest over the period covered, but smaller than may be expected, at around -7%, with a median 4% rebound in Q3 2020. The impact of the pandemic is very heterogeneous: in some industries, there is a very large decrease in utilisation (up to 93% in the air transport industry), but in some industries utilisation actually increases on the previous quarter. The relatively small impact at the median is partly because some industries were not especially affected by the lockdowns and were able to keep operating (including many business services industries) and partly due to the use-based deterioration factors in Table 2: recall that some assets have no adjustment at all.

Figure 5 – Distribution of quarter-on-quarter changes in capital utilisation by detailed industry, 2002 Q2 to 2020 Q4



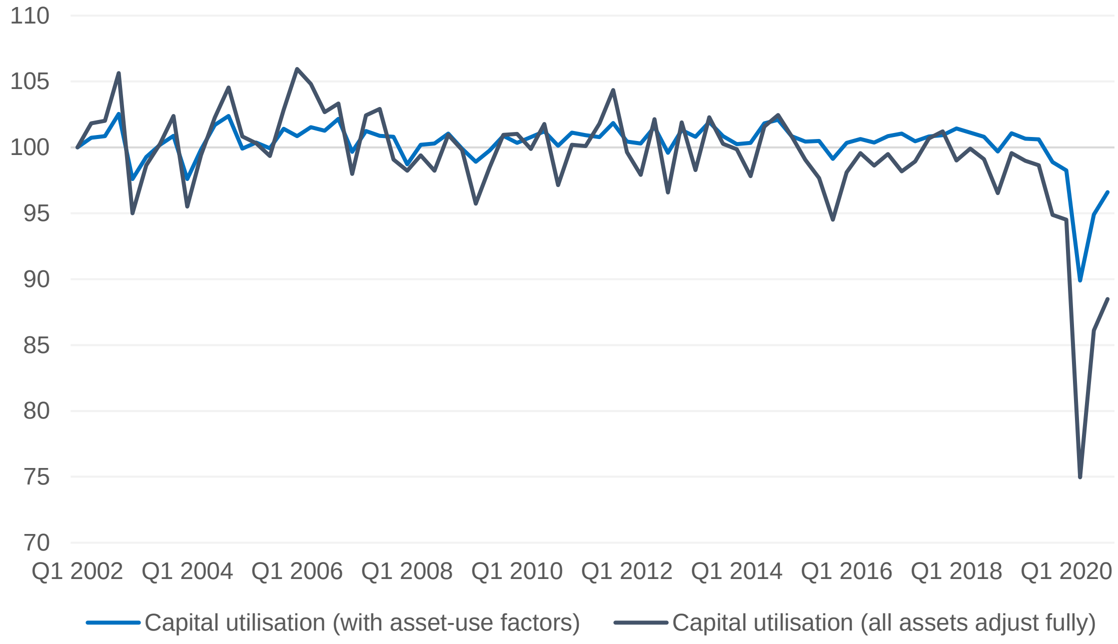
Notes: Industries are the 62 industries in the ONS MFP system – mostly 2-digit industries (divisions) from SIC 07 with some aggregations of 2-digit industries.

5.5. Sensitivity to asset-use factors

One of the most uncertain aspects of this approach are the use-based deterioration factors in Table 2, which subdue the impact of changes in hours worked on capital utilisation, and vary by asset. To assess the sensitivity of the results to these factors, Figure 6 shows the market sector capital utilisation series with and without applying these factors.

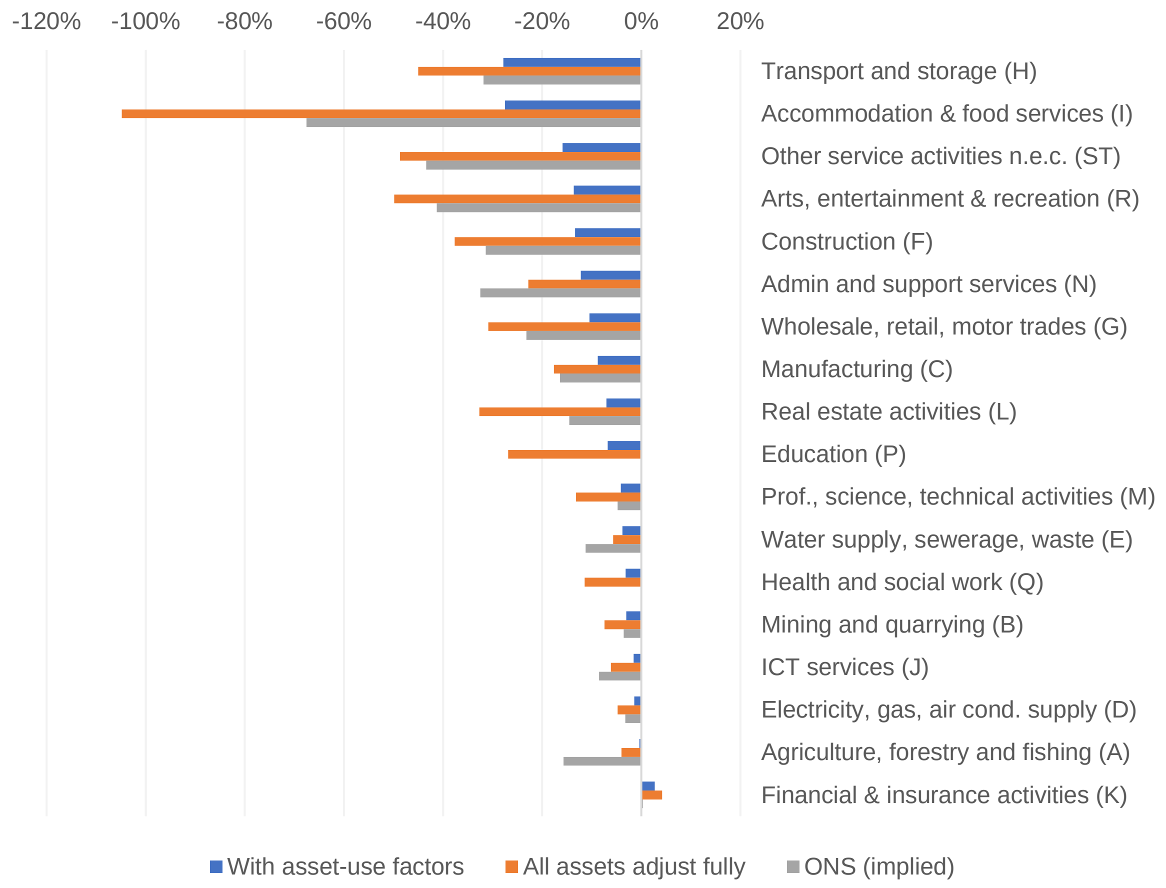
The capital utilisation series without applying the asset-use factors from Table 2 is similar to our central estimates, with the exception of the impact of the coronavirus pandemic, where it is far larger. Utilisation falls around 20% in Q2 2020 in the series without factors, and only about 10% in the version with factors; both series recover about half of their respective declines in Q3 2020. The series without factors is slightly more volatile, and falls slightly over time, especially in recent years, largely due to the larger impact of the gradual shift towards homeworking, which reduces utilisation of buildings (which have a relatively large weight).

Figure 6 – Comparison of capital utilisation series with and without asset-use factors, market sector, Q1 2002 to Q4 2020, indexed to Q1 2002 = 100



At the industry level, the impact of the factors is more significant, reflecting the differences in asset mix in each industry. Figure 7 shows the quarter-on-quarter change in capital utilisation in Q2 2020 by industry with asset-use factors, without factors (but still using the occupation-asset matching approach introduced in this paper), and the simple change in average hours worked (the standard approach used in the official MFP estimates from the ONS, as in ONS, 2021b). The approaches are well correlated across industries. The average absolute quarter-on-quarter change is smallest in the variant with asset-use factors, and largest in the variant without asset-use factors, with the standard approach somewhere between. This reflects that the occupation-asset matching relies on the industry-by-occupation data from LFS which can be more volatile, and so without the subduing effect of the asset-use factors, this can lead the method to produce more noisy results. As such, we recommend that the occupation-matching approach introduced in this paper should only be used in conjunction with the asset-use factors, which also help to subdue some of the volatility introduced by these low-level data.

Figure 7 – Comparison of capital utilisation changes by industry, with and without asset-use factors, and the standard hours-based approach, quarter-on-quarter growth rate, Q2 2020



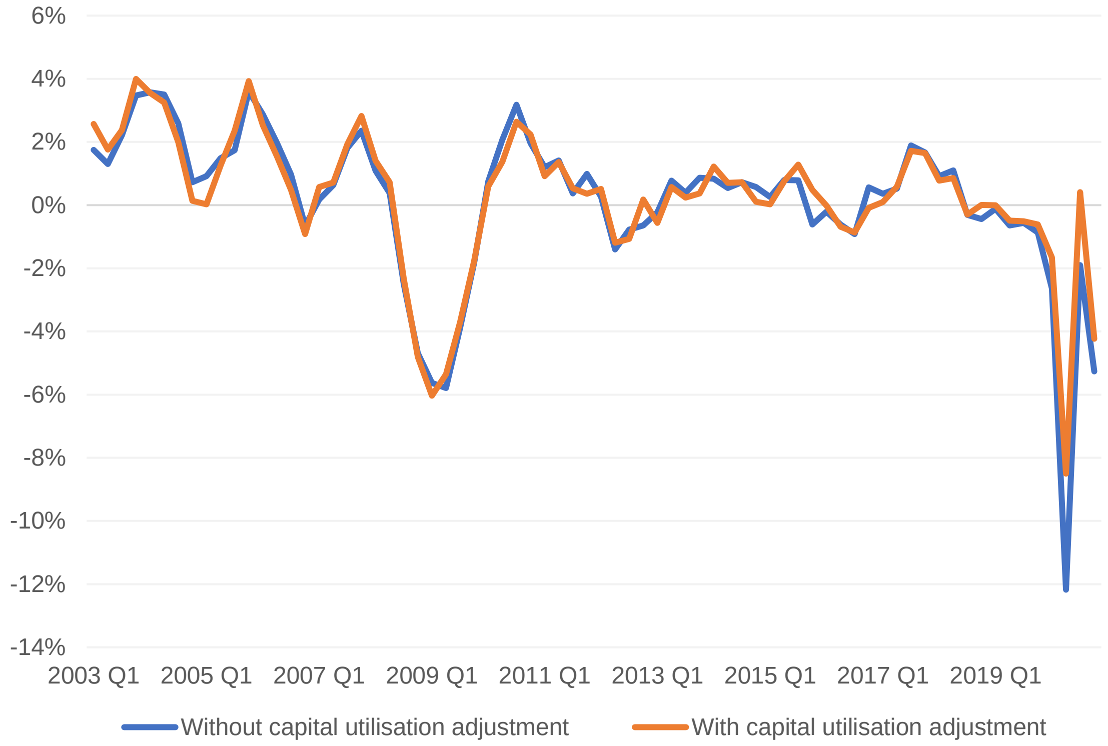
Notes: ONS data are implied from the difference between adjusted and unadjusted capital services data. No ONS estimate available for Education (P) or Health and social care (Q) due to suppressions. Data are in natural log changes, hence can be less than 100%.

5.6. Impact on MFP estimates

The impact of the adjustment on MFP estimates is small but broadly in line with expectations. Figure 8 shows quarter-on-same-quarter-a-year-ago growth rates of MFP with and without the utilisation adjustment, using the official estimates from the ONS (ONS, 2021b) as the baseline.

The introduction of the capital utilisation adjustment makes no material difference to the trend, but does lead to some small differences in MFP in a few points: a trough in growth in 2005 becomes more pronounced, and the weakness in growth in 2015 is staved off a few quarters. There is no obvious impact on the 2008/09 downturn at this level, although there are small impacts for some industries (including manufacturing). The fall during the coronavirus pandemic is moderated considerably – from around 12% to around 8% in Quarter 2 2020.

Figure 8 – Comparison of MFP growth rates with and without a capital utilisation adjustment, quarter-on-same-quarter-a-year-ago growth rates, market sector, Q1 2003 to Q4 2020



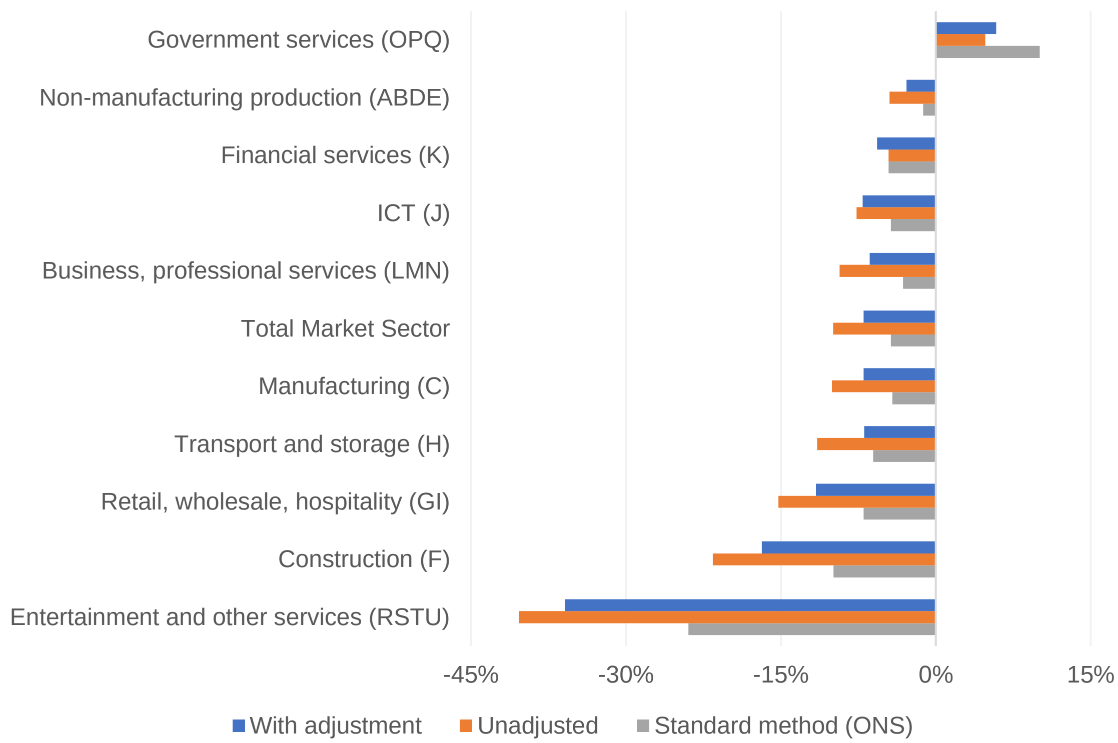
In line with the literature, the adjustment makes the MFP series less pro-cyclical (given by the correlation between the growth rates of GVA and MFP) although only slightly; this holds with and without including 2020.

The effect varies by industry according to the utilisation series and the capital intensity of the industry. Figure 9 shows the quarter-on-quarter change in MFP in Q2 2020 by industry with our central capital utilisation adjustment, without, and the standard hours-based method (as used in the official MFP estimates from the ONS, as in ONS, 2021b); this parallels Figure 7. The effect of introducing the adjustment tends to be proportionately larger in more capital intensive industries. The adjustment introduced in this paper (with asset-occupation matching and asset-use factors) tends to be less severe than the standard hours-methods (as used by the ONS), in line with the findings from Figure 8.

Correlations between output and MFP growth are weaker when applying the capital utilisation adjustments than when not, in line with the literature, in almost[18] all industries. This is true for quarter-on-quarter and quarter-on-same-quarter-a-year-ago growth rates, with and without including the pandemic period.

[18] The only exception (at this level of industry aggregation) is the government services industries (OPQ), which is fractionally better correlated – although this is a small and unusual industry group, since it is only the market sector elements of these industries, which are imperfectly measured.

Figure 9 – Comparison of MFP quarter-on-quarter growth rates by industry, with and without a capital utilisation adjustment, and the standard hours-based method, Q2 2020



6. Discussion

We believe that the methods introduced in this paper produce sensible results, with variation across assets, industries and time broadly as expected. The main shortcoming is perhaps the lack of a strong effect during the 2008/09 downturn, although this is present to a small degree in some industries. This method gives an estimate of the utilisation of capital of different types, in a conceptually improved way, using available ONS data, and on a frequency in-line with ONS productivity statistics.

The reason for the lack of 2008/09 dip is that usual hours worked respond similarly to actual hours worked in most industries, meaning the ratio between the two is largely unchanged. It is important to de-trend actual hours worked in some way, else changes over time may be due to changes in technology or productivity that lead to fewer hours being worked per person in some industries. Usual hours worked is an attractive baseline, since it relates specifically to workers and their perceptions of “usual” – allowing for changes in contracts, working arrangements and behaviours over time. It is available at the same frequency and granularity as the actual hours worked variable, and is simple to implement.

We proposed a number of adjustments to the ‘baseline’ (usual hours worked) to smooth the series against volatility and reflect the adjustment process of businesses, and adopted a four-quarter backward-looking rolling average as our central case. Doing so creates a small financial crisis effect in some industries, notably manufacturing, although this remains well below what the CBI survey measure suggests. Most other industries, and the market sector aggregate, have no visible effect. We cannot be confident that these results represent reality, as we suspect lower capital utilisation levels during, and for a time after, the 2008 downturn. However, since we are measuring an unobservable and difficult-to-measure variable, we do not have a reliable benchmark to compare against.

Another potential concern is how the approach would fair in other countries with different labour markets, especially those that had different labour market policies during the coronavirus pandemic. For instance, the US did not operate a government supported furlough scheme as in the UK, so unemployment increased far more during 2020 in the US than in the UK. However, hours worked responded similarly in both countries.

For the 'baseline' in our calculation, we use 'usual hours worked' of employed workers average over the current and preceding three quarters (i.e. a four-quarter rolling average). Since furloughed workers are still in employment, they are still asked about their 'usual hours worked' in UK labour market surveys and thus will still appear in our baseline. By contrast, in the US, since the equivalent workers will no longer be employed, their 'usual hours worked' would not be included in our baseline. As such, the measured fall in capital utilisation (the ratio between actual hours and the baseline) will be less in the US than the UK. Our four-quarter average adjustment will ensure the baseline adjusts slowly in both countries, which partly mitigates this effect, but not completely. An illustration of the effect of the baseline is in Table 5, although this is far from a full replication of the method in both countries.

Table 5 – Indicative example of baseline effect in UK and US

Variable	Units	Derivation	2019 Q1	2019 Q2	2019 Q3	2019 Q4	2020 Q1	2020 Q2	2020 Q3	2020 Q4
US										
Employment	mn	a	165.3	165.6	166.6	167.0	165.8	147.2	155.5	157.4
Actual hours worked	bn per quarter	b	69,971	69,962	70,442	70,580	69,799	61,623	65,909	67,204
Average hours worked	hours per week	c=b/a	32.6	32.5	32.5	32.5	32.4	32.2	32.6	32.9
Usual hours worked	bn per quarter	d=a*c[2019]	69,971	69,962	70,442	70,580	70,157	62,210	65,768	66,492
Baseline	bn per quarter	e=mean(d)[t:t-4]				70,239	70,285	68,348	67,179	66,157
Utilisation measure without baselining		f=b/d				1.000	0.995	0.991	1.002	1.011
Utilisation measure with baselining		g=b/e				1.005	0.993	0.902	0.981	1.016
UK										
Employment	mn	a	32.7	32.8	32.8	32.9	33.0	32.6	32.4	32.1
Actual hours worked	bn per quarter	b	13,688	13,684	13,684	13,651	13,413	10,988	11,933	12,599
Average hours worked	hours per week	c=b/a	32.2	32.1	32.1	31.9	31.3	25.9	28.4	30.1
Actual hours worked	bn per quarter	d=a*c[2019]	13,688	13,684	13,684	13,651	13,820	13,598	13,516	13,326
Baseline	bn per quarter	e=mean(d)[t:t-4]				13,677	13,710	13,688	13,646	13,565
Utilisation measure without baselining		f=b/d				1.000	0.971	0.808	0.883	0.945
Utilisation measure with baselining		g=b/e				0.998	0.978	0.803	0.874	0.929

Note: This is not a complete replication of our method as it does not include the asset-occupation matching, asset-use factors, or variation by industry. Instead it is a crude replication of the baselining method to demonstrate the effect on economy with different labour market policies during the coronavirus pandemic. Application of the method to US labour market data would yield different results.
Sources: US Bureau of Labour Statistics, UK Office for National Statistics, authors calculations

We suspect further improvements to the 'baseline' would improve matters further – using a longer window for the baseline might help.

We must also consider how these capital utilisation measures would be implemented in capital services and MFP measures. Namely, whether capital utilisation should be adjusted for across the whole time series, only at times of economic shocks or downturns, or only in the pandemic period. We outline the pros and cons of each approach in Table 5. The main argument in favour of applying this across the full time series is the consistency of approach, which removes the need to decide when to implement the adjustment. The main drawback is the potential to introduce volatility and noise into MFP measures where none already exist, as a result of volatility in the capital utilisation data; since the assumption of constant utilisation likely works reasonably well in normal times, the trade-off here is unclear. Before implementation, a thorough review of the estimated capital utilisation series in each industry would have to be conducted to ensure excessive volatility or outliers were not introduced.

Table 6 – Pros and cons to various implementation approaches in capital services and MFP measures

Approach	**Pros**	**Cons**
Implement across full time series	• Clear • No need to decide 'when counts'	• Variation outside of 'shocks' could just be noise – may reduce intelligence of MFP
Implement only during economic downturns (2008/09, pandemic, maybe others)	• Removes some pro-cyclicality in MFP • Avoids introducing noise outside of economic downturns	• Creates internal inconsistency • Requires a decision on what to implement – 'when counts'?
Implement only during the pandemic period	• Unprecedented shock – not to adjust reduces interpretability of MFP • Avoids introducing noise outside of economic downturns • No major decisions to make on 'when counts'	• Need to decide when pandemic period starts and ends • Creates internal inconsistency

This research has been carried out by ONS in response to the coronavirus pandemic, as we recognise the large impact the coronavirus pandemic has had on the UK economy, and the need for our measures of productivity to react to this. Standard measures of capital services and MFP are not responsive to shocks in the short-term, so implementing an adjustment for the change in capital utilisation may help to improve the usefulness of our MFP measures.

This paper presents a novel approach to adjust for capital utilisation, which we believe is conceptually superior to anything in the literature. We believe the matching of occupations to assets is a significant conceptual enhancement on past work, although the allocations would benefit from external review and could be further refined. The main limitations of this approach are the data quality at the low level of detail required, and the assumptions necessary in the method, which are currently not supported by sufficient evidence. However, the approach appears to produce sensible results, as shown in this paper, and the assumptions can be further researched to improve the results.

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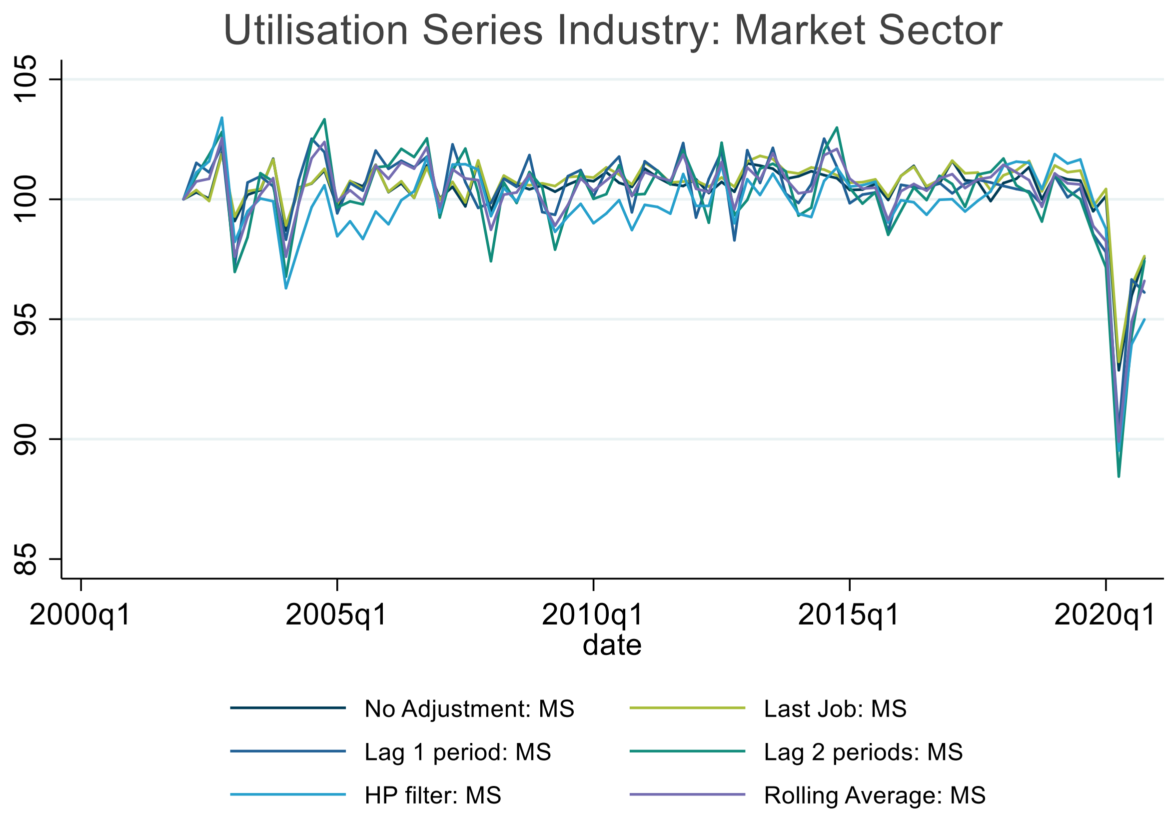
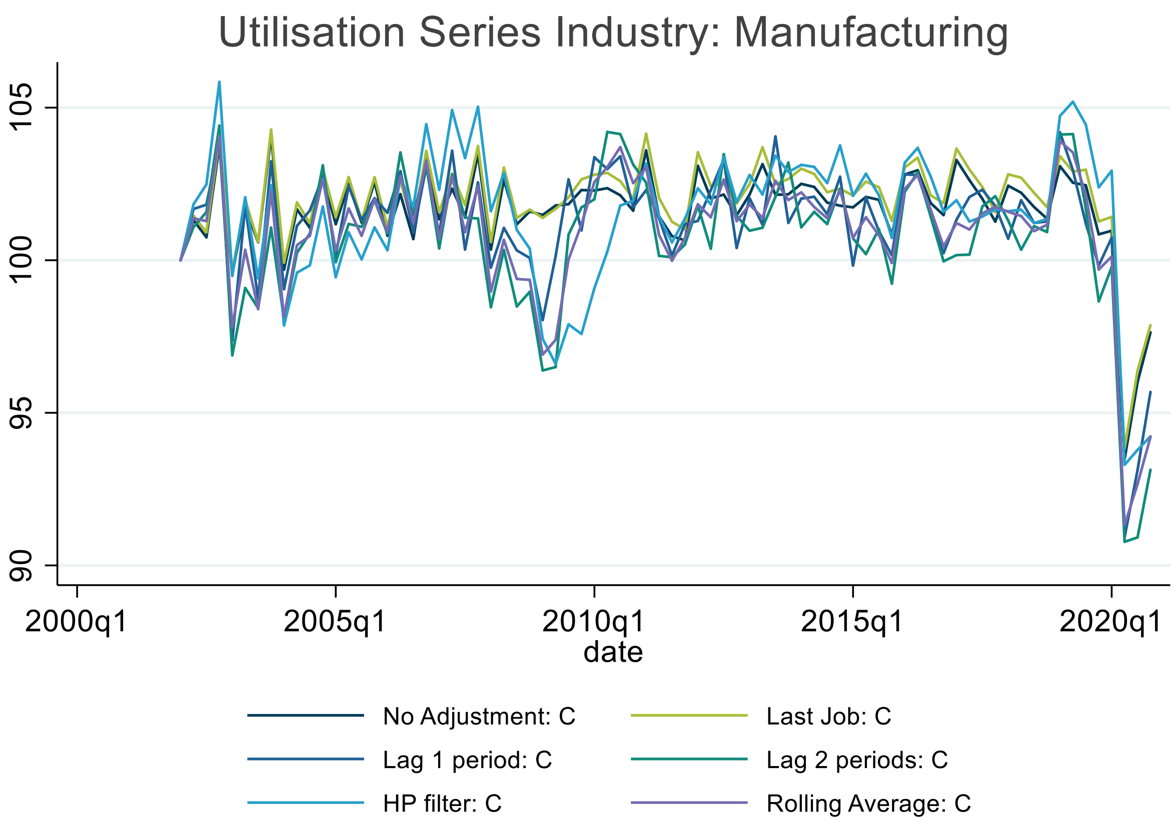
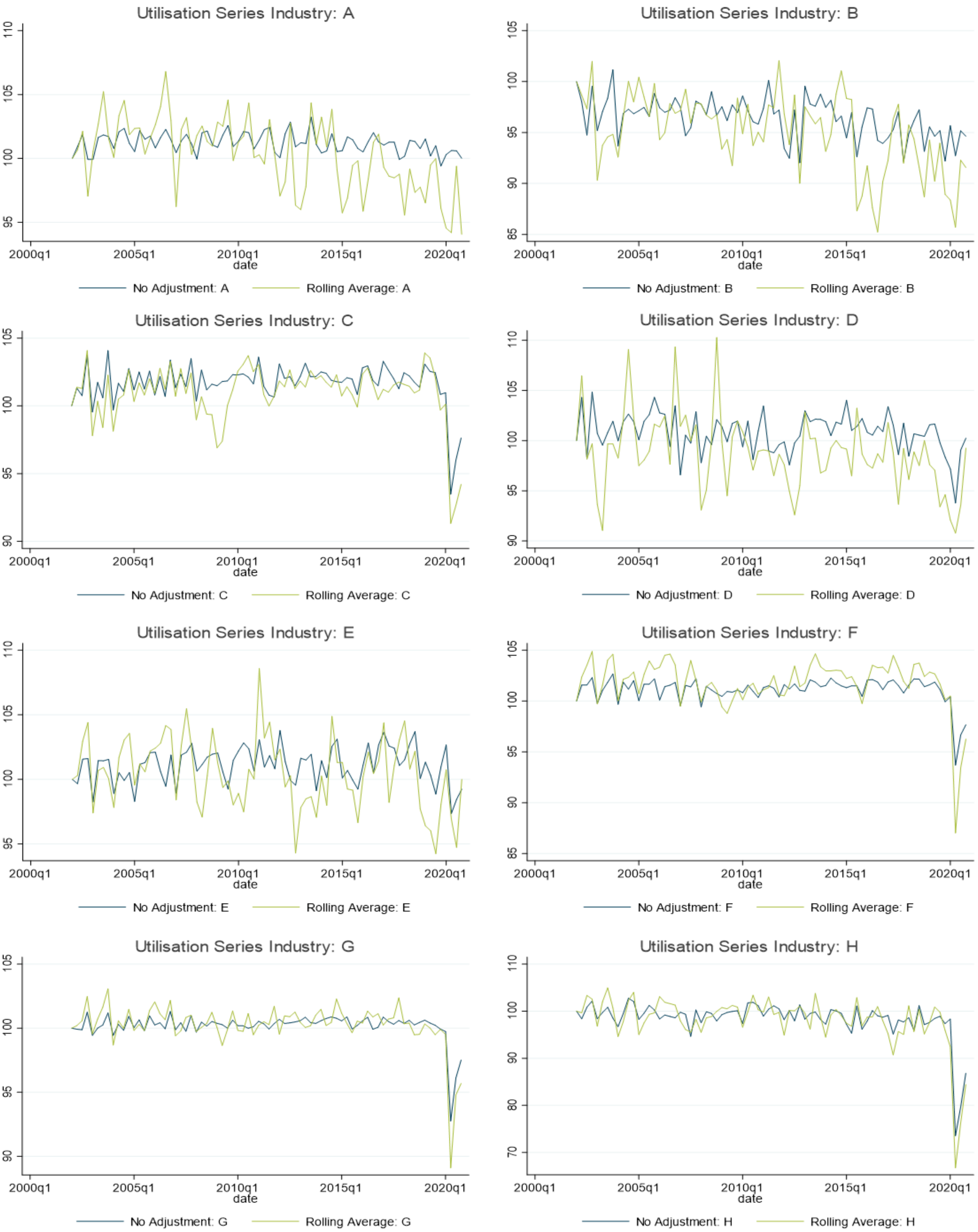
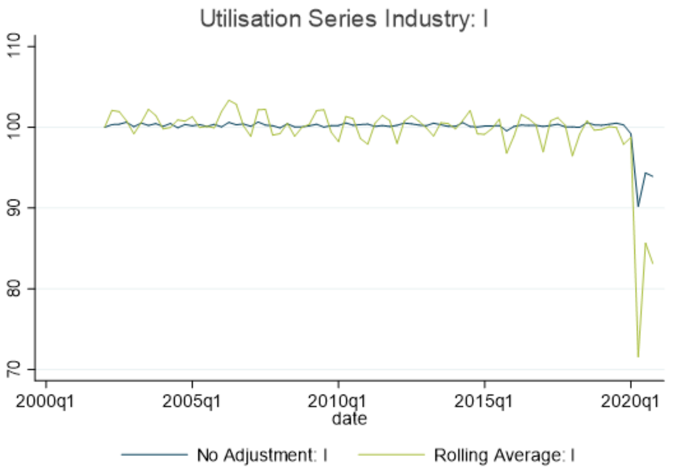
Annex 1 – Capital utilisation series, with and without four-quarter baseline adjustment, UK market sector and manufacturing, Q1 2002 = 100, Q1 2002 to Q4 2020

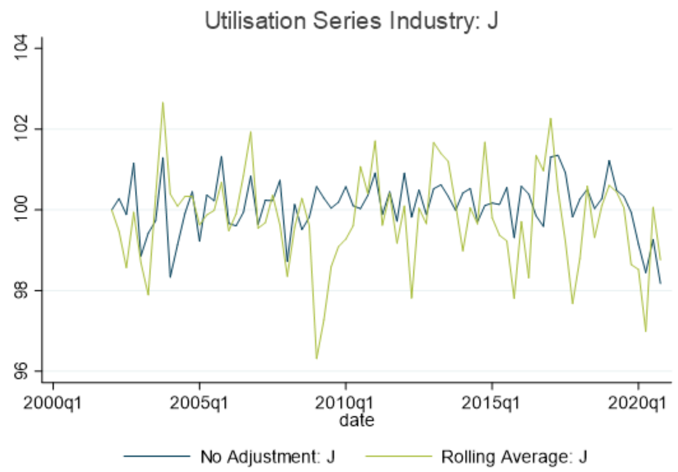


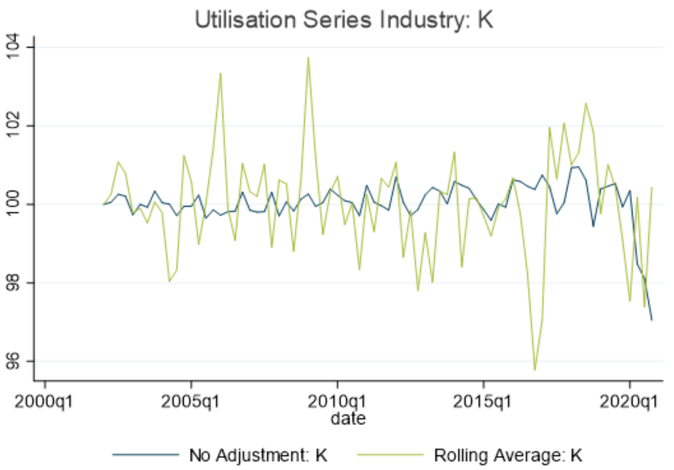


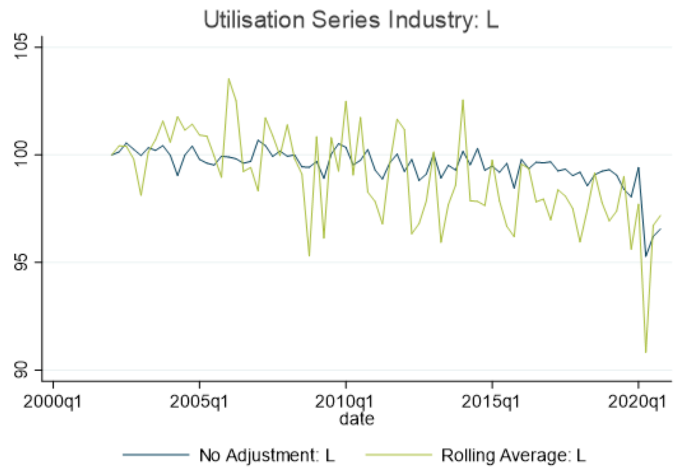
Capital utilisation series, with and without four-quarter baseline adjustment, by industry, Q1 2002 = 100, Q1 2002 to Q4 2020 Q4

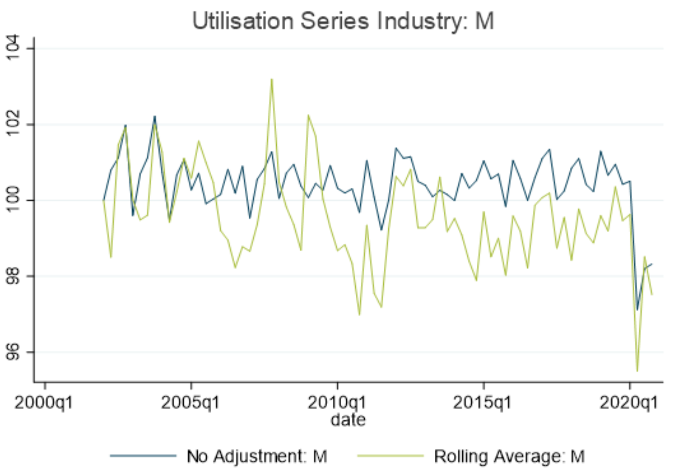


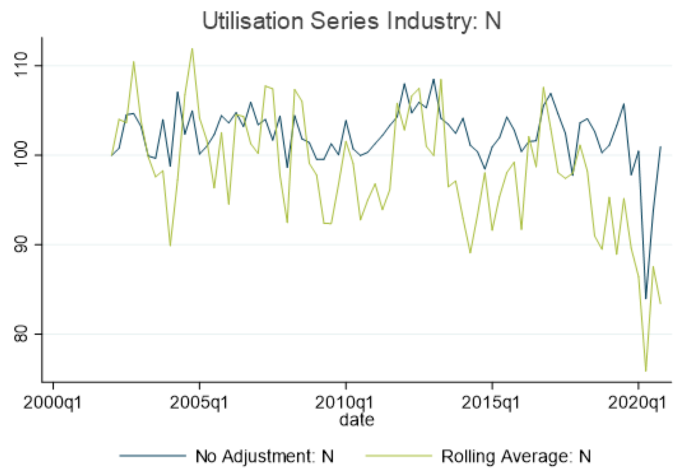

Utilisation Series Industry: I
70
80
90
100
110
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: I
Rolling Average: I

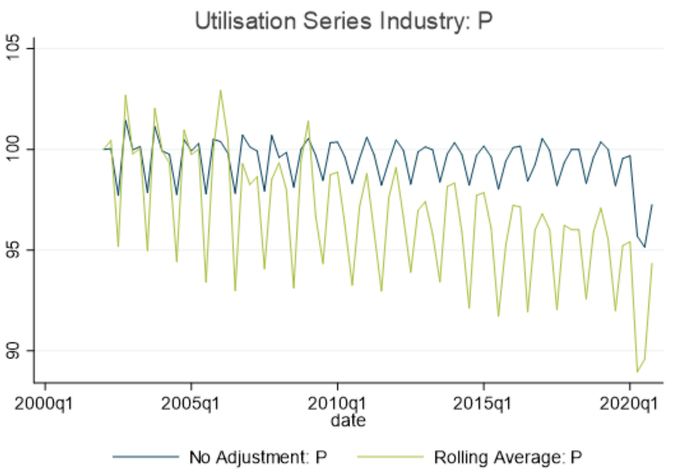

Utilisation Series Industry: J
96
98
100
102
104
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: J
Rolling Average: J

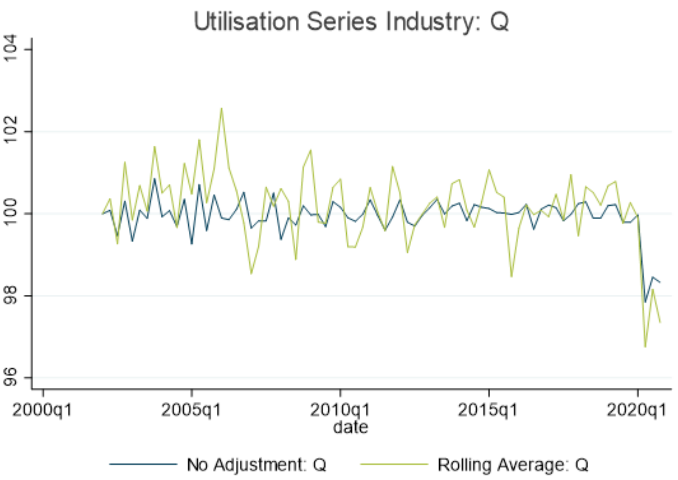

Utilisation Series Industry: K
96
98
100
102
104
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: K
Rolling Average: K

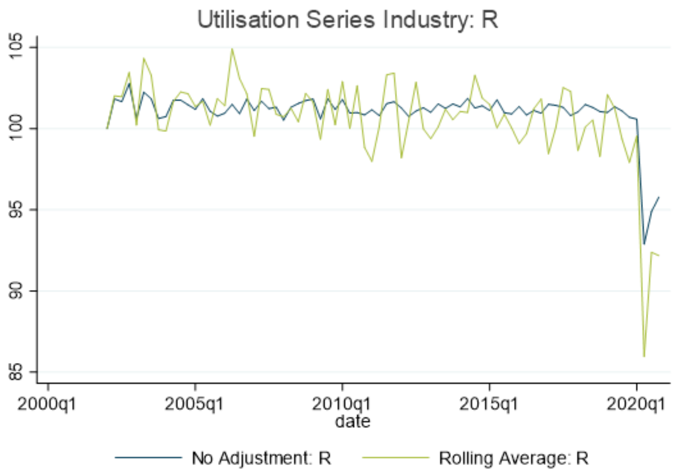

Utilisation Series Industry: L
90
95
100
105
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: L
Rolling Average: L


Utilisation Series Industry: M
96
98
100
102
104
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: M
Rolling Average: M

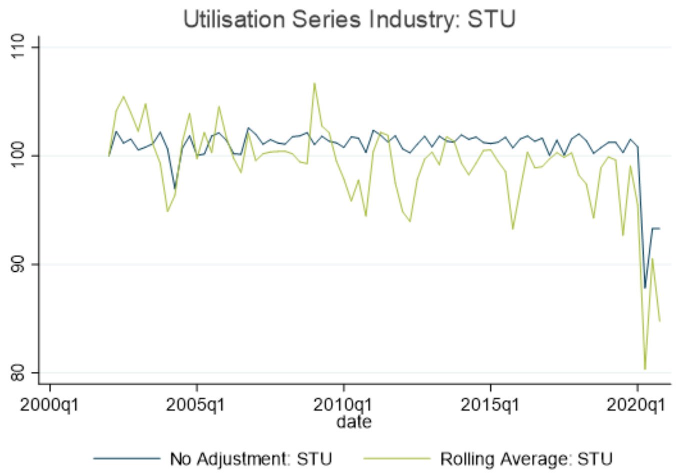

Utilisation Series Industry: N
80
90
100
110
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: N
Rolling Average: N


Utilisation Series Industry: P
90
95
100
105
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: P
Rolling Average: P


Utilisation Series Industry: Q
96
98
100
102
104
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: Q
Rolling Average: Q



Utilisation Series Industry: R
105
100
95
90
85
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: R
Rolling Average: R



Utilisation Series Industry: STU
110
100
90
80
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: STU
Rolling Average: STU

Annex 2 – Occupations matched to assets

SOC 2010 code and description	ICT hardware and software	Transport	" Heavy" OME
1115 - chief executives and senior officials	1	0	0
1116 - elected officers and representatives	1	0	0
1121 - production managers and directors in manufacturing	1	0	1
1122 - production managers and directors in construction	1	0	0
1123 - production managers and directors in mining and energy	1	0	0
1131 - financial managers and directors	1	0	0
1132 - marketing and sales directors	1	0	0
1133 - purchasing managers and directors	1	0	0
1134 - advertising and public relations directors	1	0	0
1135 - human resource managers and directors	1	0	0
1136 - it and telecommunications directors	1	0	0
1139 - functional managers and directors n.e.c.	1	0	0
1150 - financial institution managers and directors	1	0	0
1161 - managers and directors in transport and distribution	1	0	0
1162 - managers and directors in storage and warehousing	1	0	0
1171 - officers in armed forces	1	0	0
1172 - senior police officers	1	1	0
1173 - senior officers in fire, ambulance, prison and related services	1	0	0
1181 - health services and public health managers and directors	1	0	0
1184 - social services managers and directors	1	0	0
1190 - managers and directors in retail and wholesale	1	0	0
1211 - managers and proprietors in agriculture and horticulture	1	0	0
1213 - managers and proprietors in forestry, fishing and related services	1	0	0
1221 - hotel and accommodation managers and proprietors	1	0	0
1223 - restaurant and catering establishment managers and proprietors	1	0	0
1224 - publicans and managers of licensed premises	1	0	0
1225 - leisure and sports managers	1	0	0
1226 - travel agency managers and proprietors	1	0	0
1241 - health care practice managers	1	0	0
1242 - residential, day and domiciliary care managers and proprietors	1	0	0
1251 - property, housing and estate managers	1	0	0
1252 - garage managers and proprietors	1	0	0
1253 - hairdressing and beauty salon managers and proprietors	1	0	0
1254 - shopkeepers and proprietors (wholesale and retail)	1	0	0
1255 - waste disposal and environmental services managers	1	0	0
1259 - managers and proprietors in other services n.e.c.	1	0	0
2111 - chemical scientists	1	0	1
2112 - biological scientists and biochemists	1	0	1
2113 - physical scientists	1	0	0
2114 - social and humanities scientists	1	0	0
2119 - natural and social science professionals n.e.c.	1	0	1
2121 - civil engineers	1	0	0
2122 - mechanical engineers	1	0	0
2123 - electrical engineers	1	0	0
2124 - electronics engineers	1	0	1
2126 - design and development engineers	1	0	1
2127 - production and process engineers	1	0	0
2129 - engineering professionals n.e.c.	1	0	1
2133 - IT specialist managers	1	0	0
2134 - IT project and programme managers	1	0	0
2135 - IT business analysts, architects and systems designers	1	0	0
2136 - programmers and software development professionals	1	0	0
2137 - web design and development professionals	1	0	0
2139 - IT and telecommunications professionals	1	0	0
2141 - conservation professionals	1	0	0
2142 - environment professionals	1	0	0
2150 - research and development managers	1	0	0
2211 - medical practitioners	1	0	1
2212 - psychologists	1	0	0
2213 - pharmacists	1	0	0
2214 - ophthalmic opticians	1	0	0
2215 - dental practitioners	1	0	1
2216 - veterinarians	1	0	1
2217 - medical radiographers	1	0	1
2218 - podiatrists	1	0	0
4151 - sales administrators	1	0	0
4159 - other administrative occupations n.e.c.	1	0	0
4161 - office managers	1	0	0
4162 - office supervisors	1	0	0
4211 - medical secretaries	1	0	0
4212 - legal secretaries	1	0	0
4213 - school secretaries	1	0	0
4214 - company secretaries	1	0	0
4215 - personal assistants and other secretaries	1	0	0
4216 - receptionists	1	0	0
4217 - typists and related keyboard occupations	1	0	0
5111 - farmers	0	1	1
5112 - horticultural trades	0	0	0
5113 - gardeners and landscape gardeners	0	0	0
5114 - groundsmen and greenkeepers	0	0	0
5119 - agricultural and fishing trades n.e.c.	0	1	0
5211 - smiths and forge workers	0	0	1
5212 - moulders, core makers and die casters	0	0	1
5213 - sheet metal workers	0	0	1
5214 - metal plate workers, and riveters	0	0	1
5215 - welding trades	0	0	1
5216 - pipe fitters	0	0	0
5221 - metal machining setters and setter-operators	1	0	1
5222 - tool makers, tool fitters and markers-out	1	0	1
5223 - metal working production and maintenance fitters	0	0	1
5224 - precision instrument makers and repairers	1	0	1
5225 - air-conditioning and refrigeration engineers	1	0	0
5231 - vehicle technicians, mechanics and electricians	0	1	1
5232 - vehicle body builders and repairers -	0	1	0
5234 - vehicle paint technicians	0	0	0
5235 - aircraft maintenance and related trades	1	1	1
5236 - boat and ship builders and repairers	0	1	1
5237 - rail and rolling stock builders and repairers	0	1	1
5241 - electricians and electrical fitters	0	0	0
5242 - telecommunications engineers	1	0	0
5244 - tv, video and audio engineers	1	0	0
5245 - IT engineers	1	0	0
5249 - electrical and electronic trades n.e.c.	1	0	0
5250 - skilled metal, electrical and electronic trades supervisors	1	0	1
5311 - steel erectors	0	0	1
5312 - bricklayers and masons	0	0	1
5313 - roofers, roof tilers and slaters	0	0	1
5314 - plumbers and heating and ventilating engineers	0	0	1
5315 - carpenters and joiners	0	0	1
5316 - glaziers, window fabricators and fitters	0	0	1
5319 - construction and building trades n.e.c.	1	0	1
5321 - plasterers	0	0	0
5322 - floorers and wall tilers	0	0	0
5323 - painters and decorators	0	0	0
5330 - construction and building trades supervisors	1	0	0
5411 - weavers and knitters	0	0	1
5412 - upholsterers	0	0	0
5413 - footwear and leather working trades	0	0	0
5414 - tailors and dressmakers	0	0	1
5419 - textiles, garments and related trades n.e.c.	0	0	1
5421 - pre-press technicians	1	0	1
5422 - printers	1	0	1
5423 - print finishing and binding workers	0	0	1
5431 - butchers	0	0	1
5432 - bakers and flour confectioners	0	0	1
5433 - fishmongers and poultry dressers	0	0	1
5434 - chefs	0	0	0
5435 - cooks	0	0	0
5436 - catering and bar managers	1	0	0
5441 - glass and ceramics makers, decorators and finishers	0	0	1

2219 - health professionals n.e.c.	1	0	1
2221 - physiotherapists	1	0	0
2222 - occupational therapists	1	0	0
2223 - speech and language therapists	1	0	0
2229 - therapy professionals n.e.c.	1	0	1
2231 - nurses	1	0	1
2232 - midwives	1	0	1
2311 - higher education teaching professionals	1	0	0
2312 - further education teaching professionals	1	0	0
2314 - secondary education teaching professionals	1	0	0
2315 - primary and nursery education teaching professionals	1	0	0
2316 - special needs education teaching professionals	1	0	0
2317 - senior professionals of educational establishments	1	0	0
2318 - education advisers and school inspectors	1	0	0
2319 - teaching and other educational professionals n.e.c.	1	0	0
2412 - barristers and judges	1	0	0
2413 - solicitors	1	0	0
2419 - legal professionals n.e.c.	1	0	0
2421 - chartered and certified accountants	1	0	0
2423 - management consultants and business analysts	1	0	0
2424 - business and financial project management professionals	1	0	0
2425 - actuaries, economists and statisticians	1	0	0
2426 - business and related research professionals	1	0	0
2429 - business, research and admin professionals n.e.c.	1	0	0
2431 - architects	1	0	0
2432 - town planning officers	1	0	0
2433 - quantity surveyors	1	0	0
2434 - chartered surveyors	1	0	0
2435 - chartered architectural technologists	1	0	0
2436 - construction project managers and related professionals	1	0	0
2442 - social workers	1	0	0
2443 - probation officers	1	0	0
2444 - clergy	1	0	0
2449 - welfare professionals n.e.c.	1	0	0
2451 - librarians	1	0	0
2452 - archivists and curators	1	0	0
2461 - quality control and planning engineers	1	0	0
2462 - quality assurance and regulatory professionals	1	0	0
2463 - environmental health professionals	1	0	0
2471 - journalists, newspaper and periodical editors	1	0	0
2472 - public relations professionals	1	0	0
2473 - advertising accounts managers and creative directors	1	0	0
3111 - laboratory technicians	1	0	1
3112 - electrical and electronics technicians	1	0	1
3113 - engineering technicians	1	0	1
3114 - building and civil engineering technicians	1	0	0
3115 - quality assurance technicians	1	0	1
3116 - planning, process and production technicians	1	0	1
3119 - science, engineering and production technicians n.e.c.	1	0	1
3121 - architectural and town planning technicians	1	0	0
3122 - draughtspersons	1	0	0
3131 - IT operations technicians	1	0	0
3132 - IT user support technicians	1	0	0
3213 - paramedics	1	1	1
3216 - dispensing opticians	1	0	0
3217 - pharmaceutical technicians	1	0	0
3218 - medical and dental technicians	1	0	1
3219 - health associate professionals n.e.c.	1	0	1
3231 - youth and community workers	1	0	0
3233 - child and early years officers	1	0	0
3234 - housing officers	1	0	0
3235 - counsellors	1	0	0
3239 - welfare and housing associate professionals n.e.c.	1	0	0
3311 - NCOs and other ranks	0	0	0
3312 - police officers (sergeant and below)	1	1	0
3313 - fire service officers (watch manager and below)	1	1	1
3314 - prison service officers (below principal officer)	1	1	0
3315 - police community support officers	1	0	0
3319 - protective service associate professionals n.e.c.	1	1	0
3411 - artists	1	0	0
3412 - authors, writers and translators	1	0	0
3413 - actors, entertainers and presenters	0	0	0
3414 - dancers and choreographers	0	0	0
3415 - musicians	0	0	0
3416 - arts officers, producers and directors	1	0	0
3417 - photographers, audio-visual and broadcasting equipment operators	1	0	1
3421 - graphic designers	1	0	0
3422 - product, clothing and related designers	1	0	0
3441 - sports players	1	0	0
3442 - sports coaches, instructors and officials	1	0	0

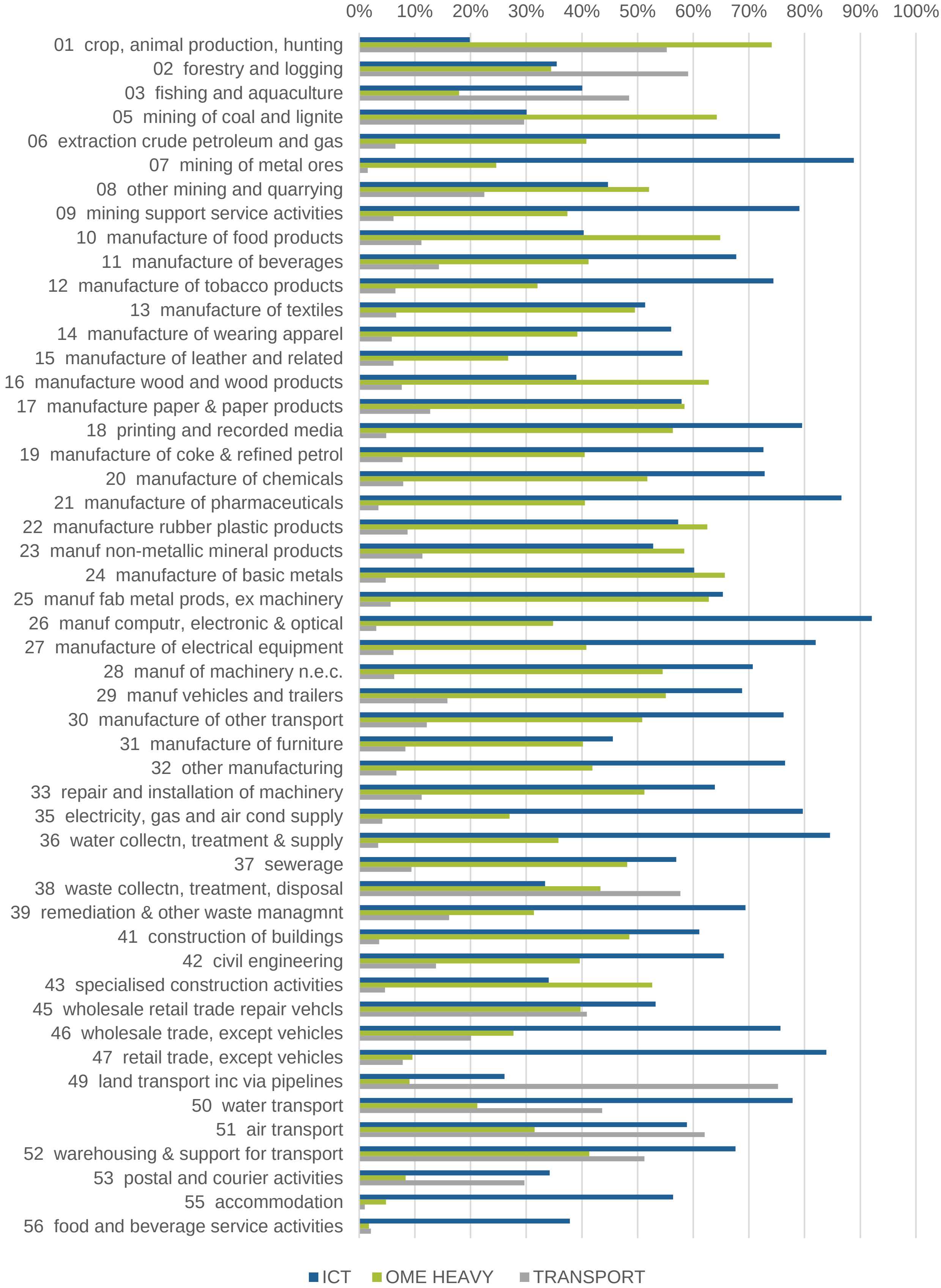
5442 - furniture makers and other craft woodworkers	0	0	0
5443 - florists	1	0	0
5449 - other skilled trades n.e.c.	0	0	0
6121 - nursery nurses and assistants	0	0	0
6122 - childminders and related occupations	0	0	0
6123 - playworkers	0	0	0
6125 - teaching assistants	0	0	0
6126 - educational support assistants	0	0	0
6131 - veterinary nurses	1	0	1
6132 - pest control officers	0	1	0
6139 - animal care services occupations n.e.c.	1	0	0
6141 - nursing auxiliaries and assistants	0	0	1
6142 - ambulance staff (excluding paramedics)	1	1	1
6143 - dental nurses	1	0	1
6144 - houseparents and residential wardens	0	0	0
6145 - care workers and home carers	0	0	0
6146 - senior care workers	1	0	0
6147 - care escorts	0	1	0
6148 - undertakers, mortuary and crematorium assistants	0	0	1
6211 - sports and leisure assistants	1	0	0
6212 - travel agents	1	0	0
6214 - air travel assistants	0	1	0
6215 - rail travel assistants	0	1	0
6219 - leisure and travel service occupations n.e.c.	1	0	0
6221 - hairdressers and barbers	0	0	0
6222 - beauticians and related occupations	0	0	0
6231 - housekeepers and related occupations	1	0	0
6232 - caretakers	0	0	0
6240 - cleaning and housekeeping managers and supervisors	1	0	0
7111 - sales and retail assistants	1	0	0
7112 - retail cashiers and check-out operators	1	0	0
7113 - telephone salespersons	1	0	0
7114 - pharmacy and other dispensing assistants	1	0	0
7115 - vehicle and parts salespersons and advisers	1	0	0
7121 - collector salespersons and credit agents	1	0	0
7122 - debt, rent and other cash collectors	1	0	0
7123 - roundspersons and van salespersons	0	1	0
7124 - market and street traders and assistants	0	0	0
7125 - merchandisers and window dressers	0	0	0
7129 - sales related occupations n.e.c.	1	0	0
7130 - sales supervisors	1	0	0
7211 - call and contact centre occupations	1	0	0
7213 - telephonists	1	0	0
7214 - communication operators	1	0	0
7215 - market research interviewers	1	0	0
7219 - customer service occupations n.e.c.	1	0	0
7220 - customer service managers and supervisors	1	0	0
8111 - food, drink and tobacco process operatives	0	0	1
8112 - glass and ceramics process operatives	0	0	1
8113 - textile process operatives	0	0	1
8114 - chemical and related process operatives	0	0	1
8115 - rubber process operatives	0	0	1
8116 - plastics process operatives	0	0	1
8117 - metal making and treating process operatives	0	0	1
8118 - electroplaters	0	0	1
8119 - process operatives n.e.c.	0	0	1
8121 - paper and wood machine operatives	0	0	1
8122 - coal mine operatives	0	0	1
8123 - quarry workers and related operatives	0	0	1
8124 - energy plant operatives	1	0	1
8125 - metal working machine operatives	1	0	1
8126 - water and sewerage plant operatives	1	0	1
8127 - printing machine assistants	1	0	1
8129 - plant and machine operatives n.e.c.	1	0	1
8131 - assemblers (electrical and electronic products)	1	0	1
8132 - assemblers (vehicles and metal goods)	1	0	1
8133 - routine inspectors and testers	1	0	0
8134 – weigher's, graders and sorters	1	0	0
8135 - tyre, exhaust and windscreen fitters	1	1	1
8137 - sewing machinists	0	0	0
8139 - assemblers and routine operatives n.e.c.	0	0	1
8141 - scaffolders, stagers and riggers	0	1	1
8142 - road construction operatives	0	1	1
8143 - rail construction and maintenance operatives	0	1	1
8149 - construction operatives n.e.c.	0	0	1
8211 - large goods vehicle drivers	0	1	0
8212 - van drivers	0	1	0
8213 - bus and coach drivers	0	1	0
8214 - taxi and cab drivers and chauffeurs	0	1	0
8215 - driving instructors	0	1	0

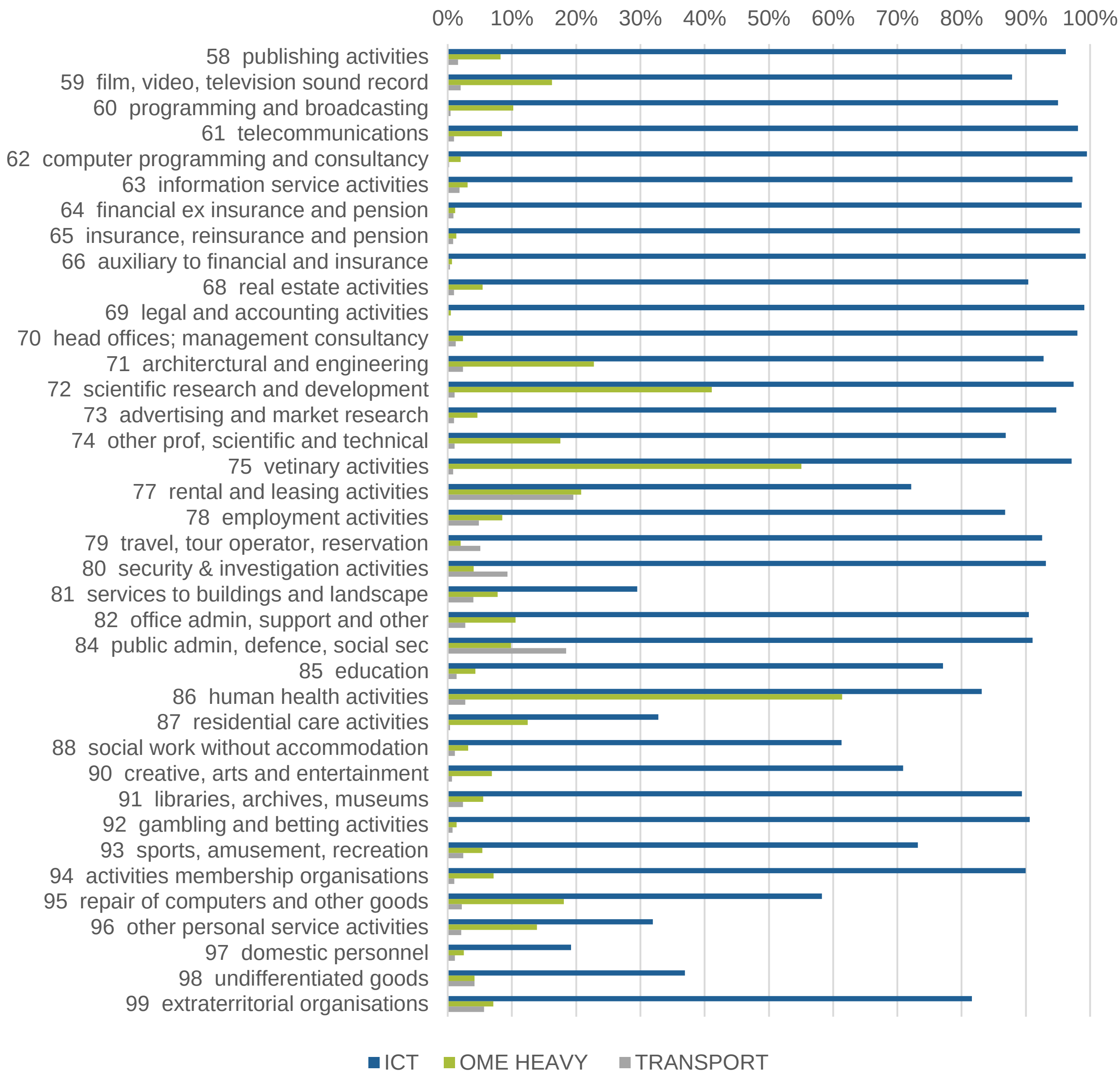
3443 - fitness instructors	1	0	0
3511 - air traffic controllers	1	1	1
3512 - aircraft pilots and flight engineers	1	1	1
3513 - ship and hovercraft officers	1	1	0
3520 - legal associate professionals	1	0	0
3531 - estimators, valuers and assessors	1	0	0
3532 - brokers	1	0	0
3533 - insurance underwriters	1	0	0
3534 - finance and investment analysts and advisers	1	0	0
3535 - taxation experts	1	0	0
3536 - importers and exporters	1	0	0
3537 - financial and accounting technicians	1	0	0
3538 - financial accounts managers	1	0	0
3539 - business and related associate professionals n.e.c.	1	0	0
3541 - buyers and procurement officers	1	0	0
3542 - business sales executives	1	0	0
3543 - marketing associate professionals	1	0	0
3544 - estate agents and auctioneers	1	0	0
3545 - sales accounts and business development managers	1	0	0
3546 - conference and exhibition managers and organisers	1	0	0
3550 - conservation and environmental associate professionals	1	0	0
3561 - public services associate professionals	1	0	0
3562 - human resources and industrial relations officers	1	0	0
3563 - vocational and industrial trainers and instructors	1	0	0
3564 - careers advisers and vocational guidance specialists	1	0	0
3565 - inspectors of standards and regulations	1	0	0
3567 - health and safety officers	1	0	0
4112 - national government administrative occupations	1	0	0
4113 - local government administrative occupations	1	0	0
4114 - officers of non-governmental organisations	1	0	0
4121 - credit controllers	1	0	0
4122 - book-keepers, payroll managers and wages clerks	1	0	0
4123 - bank and post office clerks	1	0	0
4124 - finance officers	1	0	0
4129 - financial administrative occupations n.e.c.	1	0	0
4131 - records clerks and assistants	1	0	0
4132 - pensions and insurance clerks and assistants	1	0	0
4133 - stock control clerks and assistants	1	0	0
4134 - transport and distribution clerks and assistants	1	1	0
4135 - library clerks and assistants	1	0	0
4138 - human resources administrative occupations	1	0	0

8221 - crane drivers	0	0	1
8222 - fork-lift truck drivers	0	1	1
8223 - agricultural machinery drivers	0	1	1
8229 - mobile machine drivers and operatives n.e.c.	0	1	1
8231 - train and tram drivers	0	1	0
8232 - marine and waterways transport operatives	0	1	1
8233 - air transport operatives	0	1	1
8234 - rail transport operatives	0	1	0
8239 - other drivers and transport operatives n.e.c.	0	1	0
9111 - farm workers	0	0	1
9112 - forestry workers	0	1	1
9119 - fishing and other elementary agriculture occupations n.e.c.	0	0	0
9120 - elementary construction occupations	0	0	1
9132 - industrial cleaning process occupations	0	0	1
9134 - packers, bottlers, canners and fillers	0	0	1
9139 - elementary process plant occupations n.e.c.	0	0	1
9211 - postal workers, mail sorters, messengers and couriers	0	0	0
9219 - elementary administration occupations n.e.c.	0	0	0
9231 - window cleaners	0	0	0
9232 - street cleaners	0	0	0
9233 - cleaners and domestics	0	0	0
9234 - launderers, dry cleaners and pressers	0	0	1
9235 - refuse and salvage occupations	0	1	1
9236 - vehicle valeters and cleaners	0	0	0
9239 - elementary cleaning occupations n.e.c.	0	0	0
9241 - security guards and related occupations	1	0	0
9242 - parking and civil enforcement occupations	0	0	0
9244 - school midday and crossing patrol occupations	0	0	0
9249 - elementary security occupations n.e.c.	0	0	0
9251 - shelf fillers	0	0	0
9259 - elementary sales occupations n.e.c.	0	0	0
9260 - elementary storage occupations	1	1	1
9271 - hospital porters	0	0	0
9272 - kitchen and catering assistants	0	0	0
9273 - waiters and waitresses	0	0	0
9274 - bar staff	0	0	0
9275 - leisure and theme park attendants	0	0	0
9279 - other elementary services occupations n.e.c.	0	0	0

Note: n.e.c = not elsewhere classified.

Annex 3 – Proportion of hours worked in each occupation-asset group, by industry division





Note: The above annex shows the proportion of hours worked in each occupation-asset group, by low-level industry. If an occupation is thought to use more than one asset type, their hours will contribute to both asset types total hours, meaning the proportions don't total 100%.