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

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Abstract

Most measures of productivity, especially multi-factor productivity, are pro-cyclical, due in part to a failure to account for variations in capital utilisation. The coronavirus pandemic caused a sharp decline in output and hours worked in most economies, but standard measures of capital input were largely unaffected. This motivates renewed attention on measuring capital utilisation. We propose an extension to the most common method, which uses variations in labour hours worked to proxy for variations in capital utilisation. By using only the hours worked of relevant occupations for relevant assets, we overcome a conceptual shortcoming of the standard method. 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 estimate our proposed method using UK labour market data, for 10 industries and the market sector aggregate, quarterly from 2002 to 2020. Our central estimate shows a decline in capital utilisation of around 9% in the UK market sector in the height of the coronavirus pandemic, recovering over half of this by the end of 2020. This subdues, but does not eliminate, the fall in MFP through 2020. However, the method produces less-promising results prior to 2020, particularly during the global financial crisis.

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1. Introduction

Estimates of multi-factor productivity (MFP) have long been known to be pro-cyclical, which is to say they fall during economic downturns and increase during economic booms. One reason for this pro-cyclicality is that the intensity of use (utilisation) of labour and capital vary over the business cycle, but this is largely unobserved and therefore typically not accounted for.

The coronavirus pandemic, which began in 2020, was an economic shock that resulted in large and sharp reductions in economic output across most countries of the world. While measured labour input also fell, most standard measures of capital input did not fall. The preferred measure of capital input for productivity analysis is capital services, which re-weights measures of the capital stock by an estimated user cost of capital, giving more weight to assets used more intensively in production. Both capital stocks and capital services, as usually measured by national statistical agencies and researchers, respond slowly to economic events. Since output fell sharply in 2020, but capital input as measured did not, MFP appeared to fall sharply.

In reality, the capital services input to production surely did fall, due to a fall in capital utilisation – national lockdowns to prevent the spread of the virus rendered some capital assets unusable, clearly reducing their utilisation. Adjusting capital services measures for a sharp fall in capital utilisation during 2020 would arguably better reflect reality. This would reduce or eliminate the measured fall in MFP, since now both output and inputs would fall. In order for MFP to be useful as an economic measure, it might be preferable to separate changes in capital utilisation from all the other things that MFP usually measures, including technological progress.

On the assumption that one wants to adjust for variations in capital utilisation, the question becomes how best to do so. There is a reasonable literature on this topic, but no internationally agreed approach. The most widely-used method is due to Basu, Fernald and Kimball (2006) (henceforth BFK), which uses average hours worked to proxy for variations in labour and capital utilisation, on the assumption that firms adjust along both observed and unobserved margins simultaneously. This approach is simple to implement but, we feel, has a number of conceptual drawbacks.

In this paper we develop a new conceptual framework to enhance the BFK method for estimating capital utilisation. While BFK use the hours worked of all workers to adjust capital utilisation of all capital assets, we assign types of workers (occupations) to types of capital (assets), and adjust only the relevant types of capital for variations in hours worked of only the relevant types of workers. We also restrict the variation in capital utilisation, for some assets more than others, on account of an ongoing flow of capital services even in the absence of associated hours of work.

We are particularly motivated by official statistics on MFP produced by the UK Office for National Statistics (ONS). The ONS produces (at time of writing) quarterly MFP estimates for the UK market sector, published with approximately a 3-month lag after the end of the reference quarter. As such, quarterly estimates of MFP covering the period affected by the coronavirus pandemic were being published during the period when UK government was reacting to the economic effects of the pandemic. In order for these statistics to be useful in this context, we judged it would be important for these statistics to account for the fall (and subsequent rebound) in capital utilisation.

Parts of MFP measurement in most national statistical institutes, including the UK ONS, rely on assumptions and parameters that do not vary over time or are simply unmeasured. The measured user cost of capital, part of the capital service measure, may also not respond to shocks in the short or medium run, or respond in the opposite direction to what would be expected (see Section 3.1). As such, short-run movements in capital utilisation are very unlikely to be captured in current measures. Given this, we view some merit in adjusting measures of MFP for capital utilisation, especially in times of shocks and structural breaks – the coronavirus pandemic clearly presents such an occasion.

The paper proceeds as follows. In Section 2, we provide a brief review of the literature on adjusting for capital utilisation in productivity statistics. Section 3 presents our conceptual framework for our capital utilisation adjustment, and some key parameters. 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 discusses shortcomings of the results and concludes.

2. Literature

The reason that no national statistical institutes, 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 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 five main strands, which we describe briefly below. See also Berndt and Fuss (1986) for the earliest applications, Basu, Fernald and Kimball (2006) for a discussion of the literature to that point, and Comin, Quintana, Schmitz and Trigari (2022) for an outline of more recent literature.

Labour hours worked

Arguably the most promising and widely-used method to adjust for variable capital utilisation is using some measure of hours worked of labour to proxy for utilisation of capital. This method develops from Foss (1981), Bils and Cho (1994), Shapiro (1996), Basu and Kimball (1997), Basu, Fernald and Shapiro (2001), and Basu, Fernald and Kimball (2006) (henceforth BFK). The central assumption in BFK is that profit maximising firms operate along both observed and unobserved margins simultaneously, such that variations in the observed margin (average hours worked) can proxy for variations in the unobserved margins (labour effort, and capital utilisation). The idea can also be motivated by adjustment costs (such as higher wages for labour working longer hours), and faster depreciation of capital when used more intensively (higher utilisation).

This can be interpreted intuitively – 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: true labour input is the stock of labour (employment) adjusted by a utilisation rate (average hours worked per worker); likewise, the capital measure is the stock of capital adjusted by a utilisation rate (also average hours worked per worker). Gorodnichenko and Shapiro (2011) discuss some measures other than average hours per worker that could be interpreted in a similar way, such as number of shifts, and number of temporary workers employed.

Goodridge, Haskel and Wallis (2013) implement the BFK method on annual UK data between 2001 and 2010. They find that the utilisation effect is small, with a considerably smaller coefficient on the utilisation term than in BFK for the US. While they do find a smaller fall in TFP during the 2008-09 downturn with the utilisation adjustment, reducing the degree of pro-cyclicality a little, the effect is small, and TFP is still estimated to fall considerably. Groth, Nunez and Srinivasan (2007) also apply the BFK method to data for UK industries for 1971 to 2000.

Inklaar (2007) implements the BFK method for France, Germany and the Netherlands, and compares the results with those for the US from Basu and Fernald (2001). They find that the BFK utilisation adjustment does not reduce the pro-cyclicality of TFP in services industries in the European countries, and speculate that this may be due to differences in the measurement of average hours worked across countries, or differences in labour market practices.

Fernald (2014) implements the BFK method to estimate a quarterly utilisation-adjusted TFP measure for the US market sector. This is one of few studies, to our knowledge, that apply a utilisation adjustment at quarterly frequency. The UK ONS also applied a simplified BFK-type adjustment to their official quarterly multi-factor productivity estimates for the UK during the coronavirus pandemic, described in ONS (2021b).

Intermediate inputs use

In their seminar work on US productivity, Jorgenson and Griliches (1967) applied a capital utilisation adjustment based on the use of electric motors in US manufacturing in TFP estimates for 1945 to 1965. Denison (1969) objected to the method[1], arguing that it would be inappropriate to adjust the whole capital stock of the US (across all assets and industries) by the use of electric motors in

[1] Denison also criticised the Jorgenson-Griliches utilisation measure on a range of other grounds, including the weighting procedure and implicit assumptions. The detailed criticisms of their measure are not relevant here.

manufacturing – an assumption Denison described as “truly magnificent in its implausibility” (p.22). Christensen and Jorgenson (1970) then applied the electric motors utilisation adjustment just to non-residential structures and equipment assets, resulting in a much smaller role for utilisation in US TFP.

Burnside, Eichenbaum and Rebelo (1995) use energy-usage as a proxy for capital utilisation in detailed US manufacturing industries using quarterly data. This follows the assumption that increased usage (increased utilisation) of machinery would require more energy. Basu (1996) considers materials input in a similar way.

Model-based approaches

Burnside and Eichenbaum (1996) and Larsen, Neiss and Shortall (2001) (henceforth LNS) exploit an assumed relationship between the capital stock, capital investment, and utilisation. Intuitively, when the capital-to-output ratio is low, the capital utilisation rate should be high – when there is less capital available, relative to output, it must be used more intensively. Conversely, 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 (Shapiro, Gordon and Summers, 1989).

LNS define capital utilisation as in the equation below, which is a rearrangement of Burnside and Eichenbaum’s (1996) model such that the capital-to-output ratio is more obvious.

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

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.

The model-based estimates of capital utilisation in Burnside and Eichenbaum (1996), for the US, and LNS, for the UK. track survey-based measures for capacity utilisation[2] reasonably well. In both cases the survey data cover only manufacturing industries, whereas the LNS implementation of the model covers the whole economy, so the result may not be generalisable. LNS’s capital utilisation adjustment reduces the pro-cyclicality of their measured UK TFP growth by about 50%.

Survey-based approaches

In more recent literature, Comin, Gonzalez, Schmitz and Trigari (2022) propose an estimation method that relies on a survey-based utilisation proxy: specifically, responses from firms on their current

[2] 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.

capacity utilisation given as a percentage.[3] An equivalent question has been asked of firms in services industries only since 2011, and they backcast this using the manufacturing industry data.

There is 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 and other factors of production. 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, if profit-maximising firms adjust along all margins simultaneously, as argued by BFK, then this could still be an appropriate measure of capital utilisation.

Comin et al. (2022) apply capacity utilisation adjustments to annual data for the US, Germany, Spain, France, Italy and the UK. They compare the BFK utilisation approach with an approach using survey measures of utilisation, and suggest that the survey measures produce more sensible results. Consistent with Inklaar (2007), they find that the BFK method works best in manufacturing, and in the US, but produces unintuitive results outside of manufacturing, and especially in some European countries. Their results for the UK using the BFK measure are particularly unintuitive, and while the survey-based measure gives more sensible results, they are arguably the weakest amongst the six countries they consider.

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 is similar to arguments made by Denison (1969), who describes many reasons why utilisation of capital may change, arguing that most would already be accounted for in conventional input measures of labour and capital, and others that could readily be considered as subsets of measured productivity growth. However, Denison states that he would prefer to treat such changes in capital utilisation as changes in productivity, since they do not relate to the "saving-investment process" (p.21) which governs the capital input measure, and thus capital income. This interpretation likely works well in 'normal times'.

However, this 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

[3] 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.

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. This idea is due to Berndt and Fuss (1986) and Hulten (1986). For instance, if office buildings are less beneficial to businesses after the coronavirus 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 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.

Our contribution

To summarise, the above sections give an overview of the main methods in the literature to adjust for capital utilisation. Most use measures best suited for manufacturing industries, either explicitly (survey questions that only cover manufacturing) or implicitly (use of intermediate inputs or hours worked, which are assumed proportional to capital utilisation, which both conceptually and empirically seems to work best in manufacturing). Much of the literature has been conducted in the US, and using annual data.

Our contribution to this literature is to implement a new method for calculating capital utilisation, building on the hours-based measures, in particular the BFK model. We do so by taking a more granular look into the relationship between different types of labour (occupations) and capital (assets), accounting for heterogeneity across assets, industries, and workers. In doing so we hope to address various concerns in the literature, including that relevance of the utilisation measures outside of the manufacturing industry. We also do so at quarterly frequency, unlike many past studies.

We sidestep the philosophical debate, and consider options to adjust for capital utilisation, on the assumptions that one does wish to. We critique the ‘model response’ view in the context of current measurement in Section 3.1.

3. Conceptual framework and approach

In this section we outline the growth accounting framework and how a capital utilisation adjustment enters, the problems we see with the ‘standard’ hours-based approach of BFK, 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 national statistical institutes 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 aggregator function for types of capital k, and A 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[4] considers types of labour l that differ by age, sex, education and/or industry, with aggregation by their shares of total labour renumeration.

We use ONS growth accounting estimates throughout, applying our capital utilisation adjustment onto existing official measures. ONS follow standard practice and international guidance (e.g. OECD, 2001), and 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), and α is the output-elasticity of labour. As is standard, ONS use the labour share of income that predominates in the industry for α, which varies over time. 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[5], and capital income is gross operating surplus (capturing consumption of fixed capital and net operating surplus) and the capital share of mixed income.

Taking logs and differentiating equation (2) with respect to time, and let Δ denote 'change in the natural log', then the change in output is given by:

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

The capital aggregator function K is 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.

[4] The functional form of the labour aggregator function is not central to the argument, so we omit it for brevity.
[5] 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 capital services measure is constructed as 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:

$$\Delta K_{i,t} \ = \sum\nolimits_{a} \left(\Delta PS_{i,a,t}\right) \times \overline{UCS}_{i,a,t} \tag{4}$$

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 the user cost of asset a in industry i at time t, divided by total user costs 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 calculated using the Perpetual Inventory Method (PIM) whereby a time series of investment data is cumulated, retired and depreciated. The key inputs are long time series of current price capital investment data (with breakdowns by industry and asset), suitable price indices (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. See ONS (2020) for details on the measures we use here.

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 depreciation). 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 investment in 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 national statistical institutes, including ONS[6], to ensure consistency within the framework. It can also be given exogenously, often based on market rates. On

[6] ONS use a single rate of return across the market sector, rather than one that varies by industry. See ONS (2020) for details.

the assumption of profit maximisation behaviour, 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 conceptually capture both 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 depreciation rates is likely to be missed. We return to this in Section 3.5.
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 be recorded in real time, and would likely 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 rarely, if ever, be the case. As such, we proceed to think about implementing a capital utilisation adjustment in the context of current measurement.

3.2. Introduction a capital utilisation adjustment into the capital services measures

We modify the capital services measure K to account for utilisation by including a multiplicative factor U for each industry[7]:

$$\Delta\widetilde{K}_{i,t} = \left(1 + \Delta K_{i,t}\right) \times \left(1 + \Delta U_{i,t}\right) - 1 \qquad (6)$$

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[8] 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.

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 $\Delta\widetilde{K}_{i,t} = \Delta K_{i,t}$.

The industry capital utilisation measure is constructed as a Törnqvist index, using two-period rolling average user cost shares, to weight the growth of asset utilisation measures within each industry. The growth of this index is then:

$$\Delta U_{i,t} = \sum_{a} \left(\Delta U_{i,a,t}\right) \times \overline{UCS}_{i,a,t} \qquad (7)$$

Where $\Delta U_{i,a,t}$ is the (change in the) capital utilisation measure in industry i, of asset a, at time t. This gives an aggregate capital utilisation index for each industry. Note that for some assets we will assume constant utilisation, that is $\Delta U_{i,a,t} = 0$.

[7] This can also be applied at the asset level to give a capital services index for an asset across industries, e.g. $\Delta\widetilde{K}_{a,t} = \left(1 + \Delta K_{a,t}\right) \times \left(1 + \Delta U_{a,t}\right) - 1$. For brevity, we assume application at the industry level going forward.

[8] 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.

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, consistent with the unadjusted capital services measure in (4), 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.

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 to capital utilisation adjustment

While an hours-based approach to capital utilisation adjustment (as in BFK) 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 (BFK) 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 asset. 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 – 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 (BFK) 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, even though the woodworker does not use computers. Again, this is a shortcoming of the standard method.

Most obviously, the standard (BFK) 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 (which produce income based on the behaviour of consumers, rather 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 over 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[9], average hours worked have been on a steady downward trend over the long run. 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, and therefore want to abstract away from them to leave just cyclical variation. Comin et al. (2022) make a similar point regarding movement in hours worked for reasons other than changes in utilisation, especially regulatory changes.

In sum, the standard hours -based method (the BFK 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 near one-to-one, and there is 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, an argument also made by Inklaar (2007).

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

[9] 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.

specific assets such as transport equipment or machinery, we select only a subset of occupations. This overcomes the issue described above, whereby all workers are assumed to use all capital equally – now, only the hours of relevant occupations will be considered, and the hours worked of other occupations will 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 coronavirus pandemic, since workers that can work from home are likely not those that will be needed to use assets *in situ*.

A summary of the occupations matched to the assets in this method are given in Table 1 (see Section 4.1 and Annex B for more). 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 period of the coronavirus pandemic). 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 3.5) so do not have occupations matched.

The most challenging asset class is 'other machinery and equipment' (OME) which covers a very heterogenous set of assets, including manufacturing machinery, medical equipment, industrial cleaning equipment, mining and agricultural machinery and equipment, fixtures and fittings (e.g. lighting equipment), 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 fixtures and fittings, office furniture, shelving and storage equipment, etc.

In many services industries in the UK, "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).

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 distinct definitions (ICT equipment and software, "heavy" OME, and transport equipment) is in Annex B.

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 3.3: 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 depreciation 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 worked 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:

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

Where $r_{i,a,t}$ is the ratio of actual hours worked to a baseline measure 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 or by industry by assumption). Recall that for some assets we assume constant utilisation, that is $\frac{r_{i,a,t}}{r_{i,a,t-1}} \equiv 1$.

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

$$\Delta U_{i,t} \ = \sum\nolimits_a \left(\Delta U_{i,a,t}\right) \times \overline{UCS}_{i,a,t}$$

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, we believe, many of the shortcomings of the standard hours-based method (the BFK 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

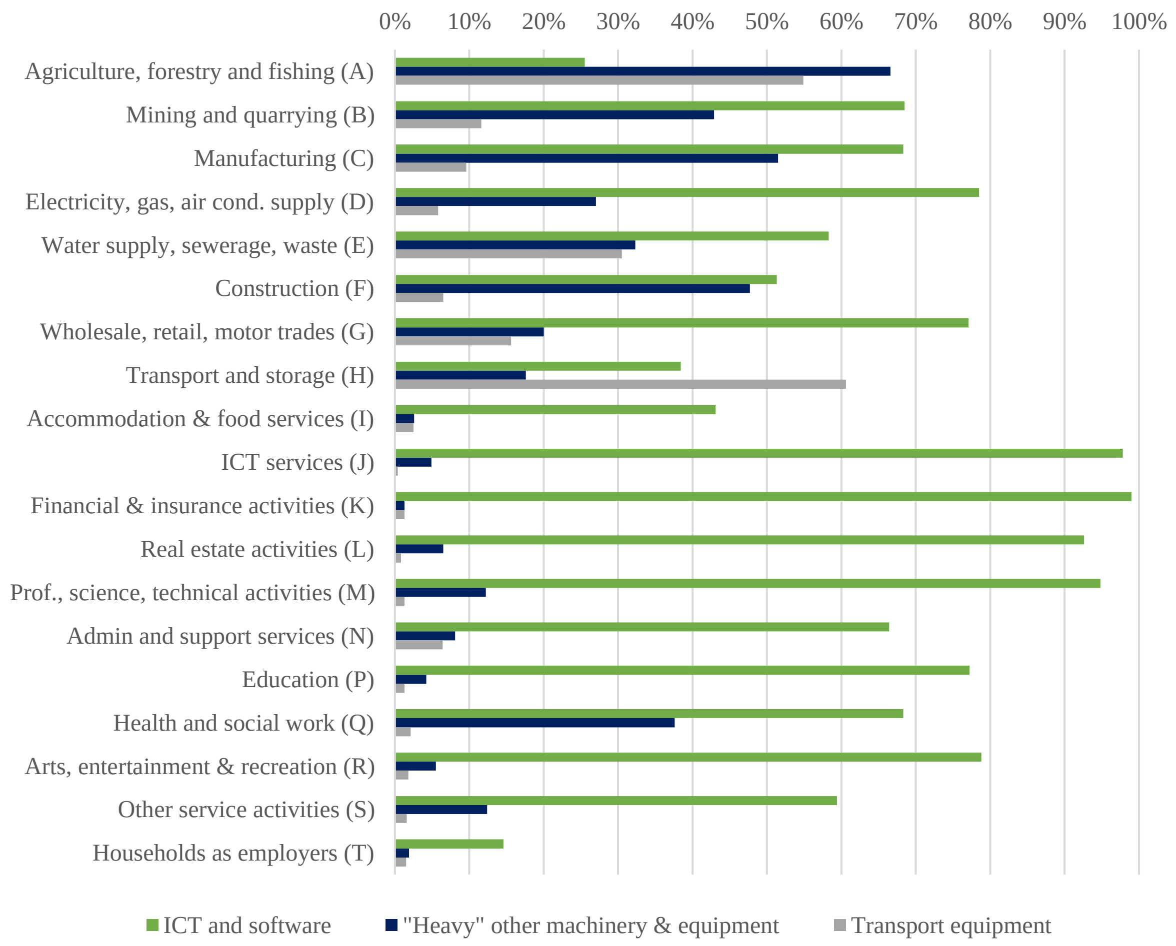
In this section we discuss the methods and data used to estimate the series described in Section 3, namely the assignment of occupations to assets, and the estimation of hours worked of these groups (including office-hours worked).

4.1. Assignment of occupations to assets

We assigned each of the 369 Unit Group occupations (4-digit level) from the UK Standard Occupation Classification (SOC) 2010 to the asset classes used in ONS capital stocks and capital services measures, using our judgement guided by a number of resources. First, in order to gain a detailed understanding of the nature of the assets, we used the descriptions of assets given in international guidance, including the European System of Accounts (ESA) 2010 (Eurostat, 2010), the System of National Accounts (SNA) 2008 (United Nations *et al.*, 2009), OECD Measuring Capital Manual (OECD, 2009), and the Classification of Products by Activity (CPA) revision 2.1. 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. Finally, we used data from the US O*NET database on the tasks performed by detailed occupations, constructing measures of asset use and converting the data to the UK occupational classification. More details of the sources and process are given in Annex B.

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 hours worked in 2018.

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



Source: UK Labour Force Survey, authors' calculations.
Notes: Letters given in brackets are sections of the UK Standard Industrial Classification (SIC) 2007. See Table 1 for associated occupation types, and Annex B for more details on the assignments, and more detailed industry results.

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).[10] 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 "heavy" OME share, reflecting medical machinery and equipment. Note that the industry aggregation used in Figure 1 hides some variation at lower levels, shown in Figure B1 in Annex B.

4.2. Estimating hours worked

We estimate hours actually worked of these asset-occupation groups at quarterly frequency using data from the UK 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: the ratio of hours actually worked to 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 estimated 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.[11] Following ONS (2021a), we define four homeworking statuses, based on three homeworking questions:

- Mainly work away from the office – respond that the place they 'mainly work' is *not* "separate to their home" (such as 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

[10] Public admin (O) also has a relatively large transport share, which is likely due to the police and military in this industry. However, since our measures focus on the market sector, we omit section O entirely.
[11] Some of the necessary variables are collected from only from Wave 1 respondents, and are therefore available only in the Annual Population Survey (APS) dataset. We combine the necessary variables from the APS dataset with the quarterly LFS responses, merging on personal identifiers.

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

We then assign a fraction of each person's hours worked to be homeworking hours, depending on their homeworking status, as shown in Table 3. Our buildings utilisation measure is based on all hours worked that are not estimated as homeworking hours. 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).

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 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%	

Source: authors' judgement, informed by various sources including Felstead and Reuschke (2020).

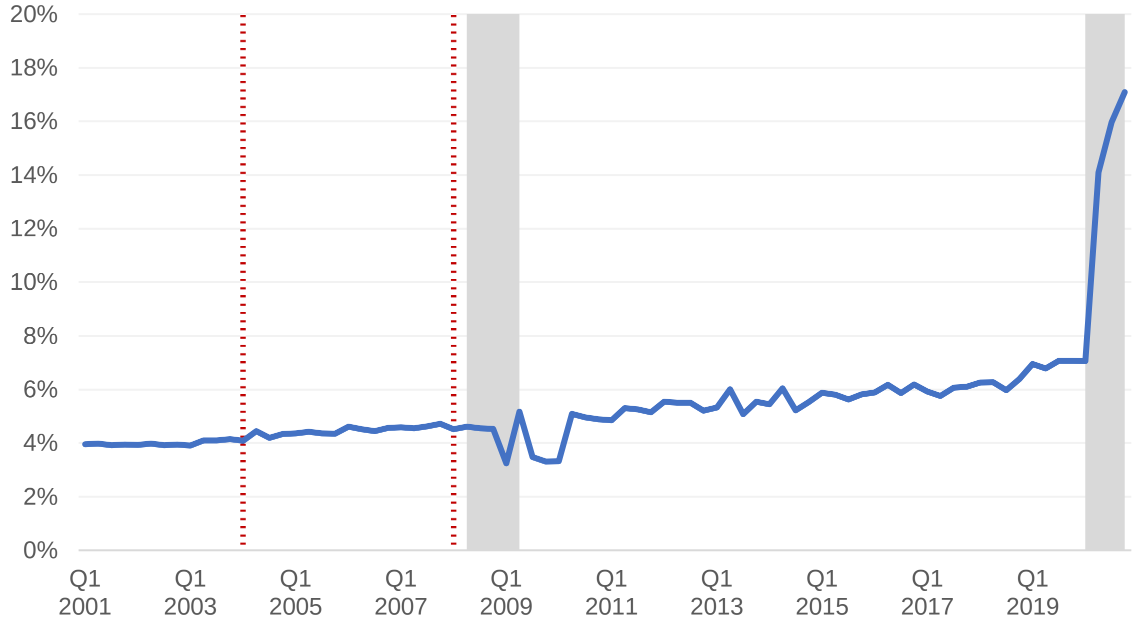
Although buildings make up a large fraction of the capital stock in the UK, they make up a smaller fraction of the capital services index (due to their relatively lower weighting in user costs) and a yet smaller impact on our capital utilisation measure. This is because of the use-based deterioration 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 utilisation measure for buildings. This rises slowly over time, from around 4% in the early 2000s, to about 6-7% in recent years. The economic downturn is visible in this data, albeit with an unusual pattern, and the coronavirus pandemic results in a massive increase in homeworking.

The trends by industry (not shown) are as expected, with industries like professional services and ICT industries, which employ relatively more occupations that are better able to work from home, 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 methods changes and classification conversions occasionally cause increased volatility in the back series.

In comparison to other sources, our estimates may underestimate the ‘true’ fraction of hours worked at home during the pandemic due to the wording of the homeworking questions on the LFS. Respondents that did not work from home before the coronavirus pandemic, but did so due to national lockdowns during 2020, may not have responded that they “mainly” worked from home. The relevant question on the LFS refers to the respondent’s “usual” place of work, and respondents might have considered their status at that time as ‘unusual’. Instead, they might say that they worked from home in the reference week, but did not mainly work from home – in this case, we would allocate only 25% of their hours to homeworking (Table 3). This might be a reasonable assumption pre-pandemic, but certainly not during 2020, when workers were mostly entirely working from home, or entirely working away from home (or on furlough). We do not vary the factors in Table 3 over time given lack of data on which to calibrate such an adjustment.

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



Source: UK Labour Force Survey, authors’ calculations.
Notes: Breaks in methods 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.

Following the coronavirus pandemic, the ONS has made changes to the LFS, and now asks the number of hours an individual works remote. As such, implementing our method in future could use a more accurate measure of homeworking hours. One benefit of the LFS is the long and relatively consistent time series it allows, necessary to apply our method over time.

Alternative methods of measuring the homeworking rates, such as the ONS-run Opinions and Lifestyles Survey[12], estimate around 35% of individuals are working fully from home with a further 10% working at least some of their hours from home report in 2020 Q4, the last quarter shown in Figure 2. This could suggest that the 'true' fraction of hours worked from home could be larger than we present.

An underestimate of homeworking hours in our estimates would mean that the utilisation of non-residential buildings would not fall enough. However, an underestimate of homeworking (an overestimate of utilisation of non-residential buildings) might be preferable, since it would offset the (unmeasured) role of "potential capital", as proposed by Eberly, Haskel and Mizen (2021). They argue that capital owned by households, such as residential dwellings, home office furniture, etc. are unmeasured capital inputs that are used to a greater extent during the pandemic due to increased homeworking.

4.3. Adjusting the baseline

It is important to de-trend actual hours worked in some way, else changes over time may reflect changes in technology or productivity that lead to fewer hours being worked per person in some industries, instead of variation in capital utilisation. 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 of the two (and hence the utilisation measure) 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 filter (such as a Hodrick-Prescott 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

[12] In the Opinions and Lifestyle Survey respondent were asked: "In the past seven days, have you worked from home because of the coronavirus (COVID-19) pandemic?" and "In the past seven days, have you left home for any of the following reasons?" where "work" was included as an option. Working status can then be derived from these two questions.

already complicated process, and could lead history to be revised with every 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 for the US (e.g. Fernald, 2014) who uses this 'de-trending' approach. We look to avoid this issue.[13]

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 baseline – 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 long the lag or average should be, although some choices are intuitive.

We tested five 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).

Figure A1 in Annex A 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. Figure A2 in Annex A also shows our central case (using the four-quarter backward looking rolling average of usual hours as the baseline) and the 'no adjustment' (using the contemporaneous usual hours worked data) for each SIC 2007 industry section (letter-level industry).

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

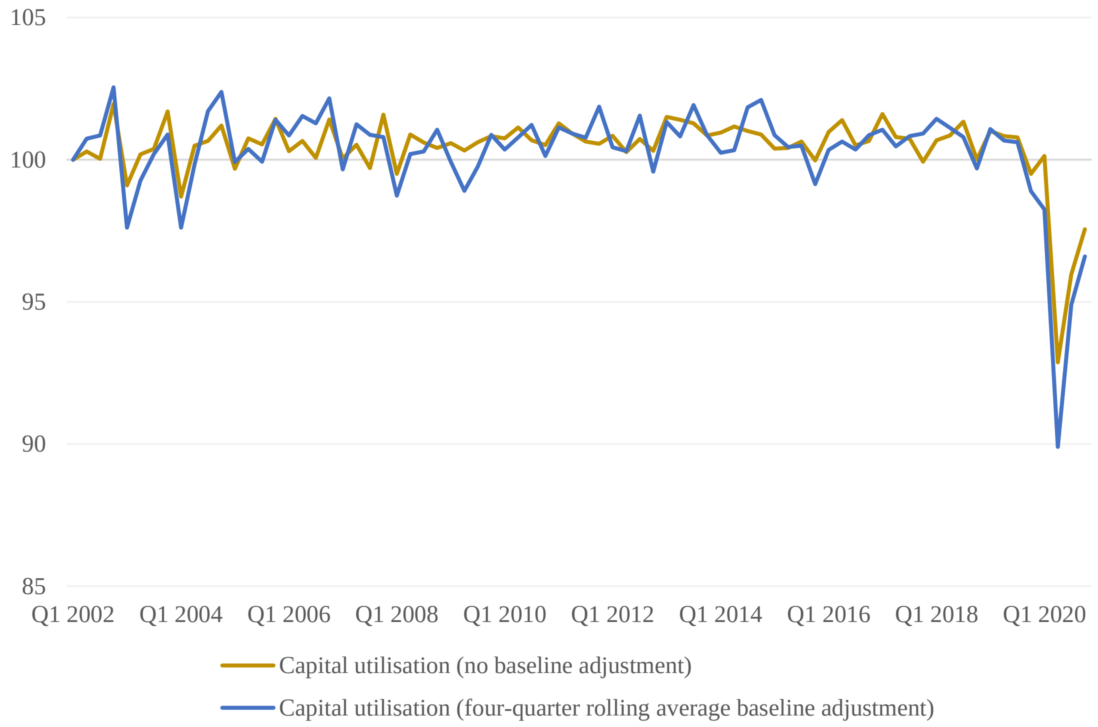
5. Results

5.1. 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 system (ONS, 2021b) 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 3.6 for algebra). Figure 3 shows the market sector capital utilisation series, indexed to Quarter 1 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, not seasonally adjusted, indexed to Q1 2002 = 100



Source: UK Labour Force Survey, ONS, authors' calculations.
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 3.6 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.[14] 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 does not appear to be 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 our hours-based utilisation measures, 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. 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

Table 4 – Seasonal characteristics of the utilisation adjustments

Quarter	Average quarter-on-quarter utilisation change, whole economy	Number of industries consistent with whole economy change	Median quarter-on-quarter utilisation change, across industries	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

Source: UK Labour Force Survey, ONS, authors' calculations.
Notes: Averages 2002 to 2019.

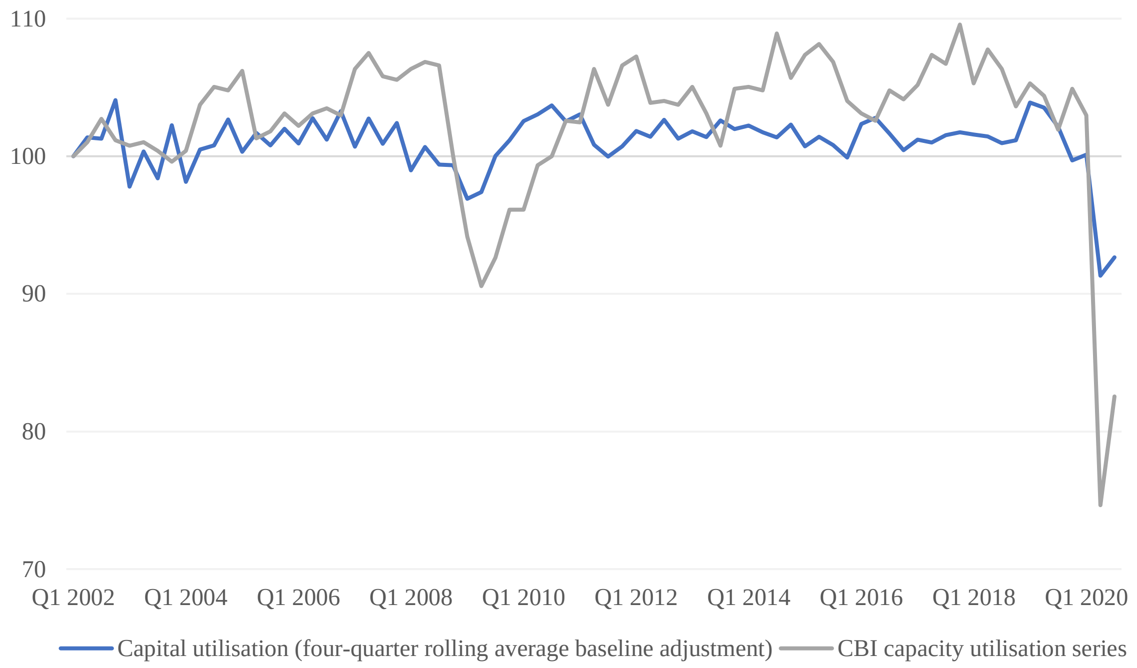
[14] Note that the series are not seasonally adjusted, and we might see a larger effect on a seasonally adjusted basis.

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.

5.2. 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 period of the coronavirus pandemic, the series are essentially unalike – the CBI series is far more cyclical than our 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, not seasonally adjusted, indexed to Q1 2002 = 100



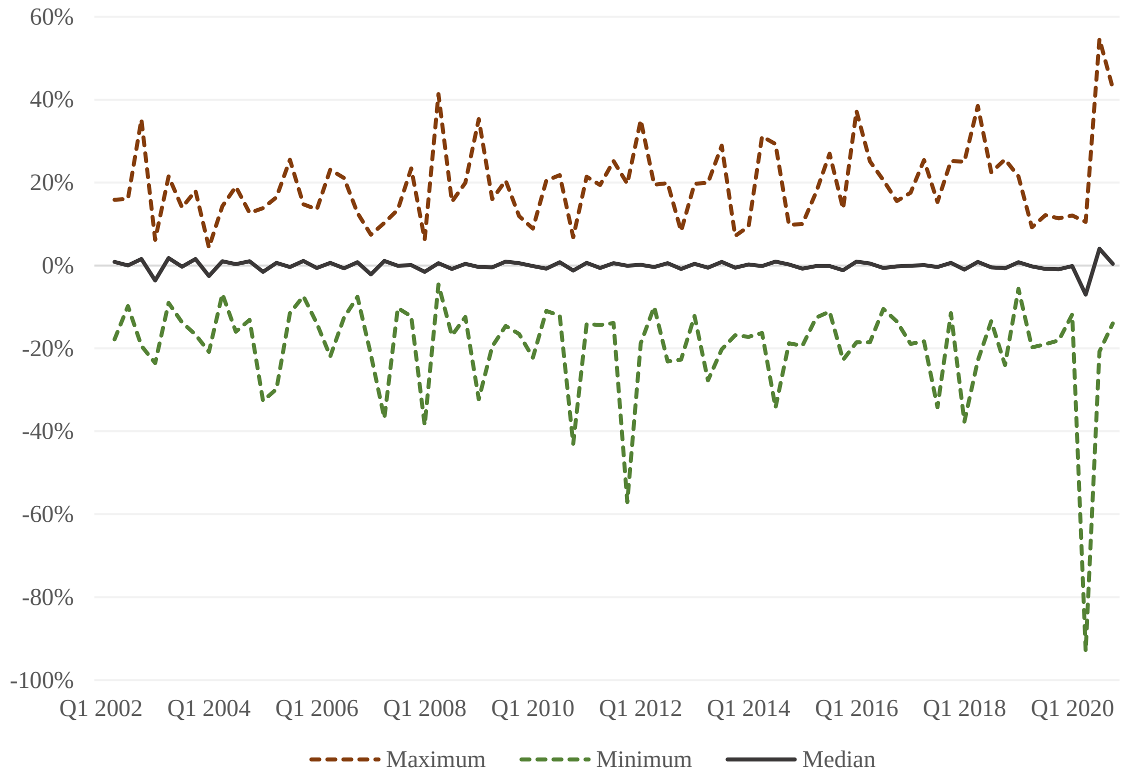
Source: Confederation of British Industry (CBI), UK Labour Force Survey, ONS, authors' calculations.

Figure 5 shows the median, minimum and maximum quarterly change across the 62 industries[15] 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 coronavirus pandemic is very heterogeneous: in

[15] These are largely industry divisions of SIC 2007, with some aggregations thereof.

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 median impact is partly because some industries were not especially affected by the national 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



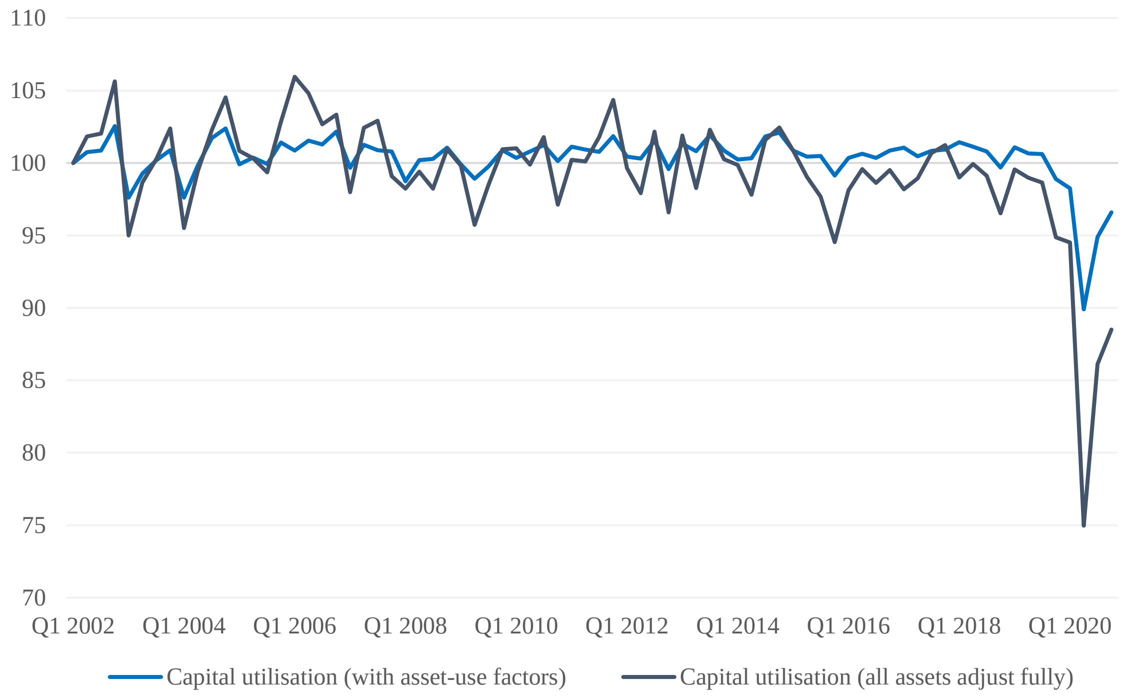
Source: UK Labour Force Survey, ONS, authors' calculations.
Notes: Industries are the 62 industries in the ONS MFP system – mostly two-digit industries (divisions) from SIC 07 with some aggregations of 2-digit industries.

5.3. Sensitivity to asset-use factors

One of the most uncertain aspects of our approach is 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, not seasonally adjusted, indexed to Q1 2002 = 100



Source: UK Labour Force Survey, ONS, authors' calculations.
Notes: both series use the four-quarter backward looking adjustment to the baseline.

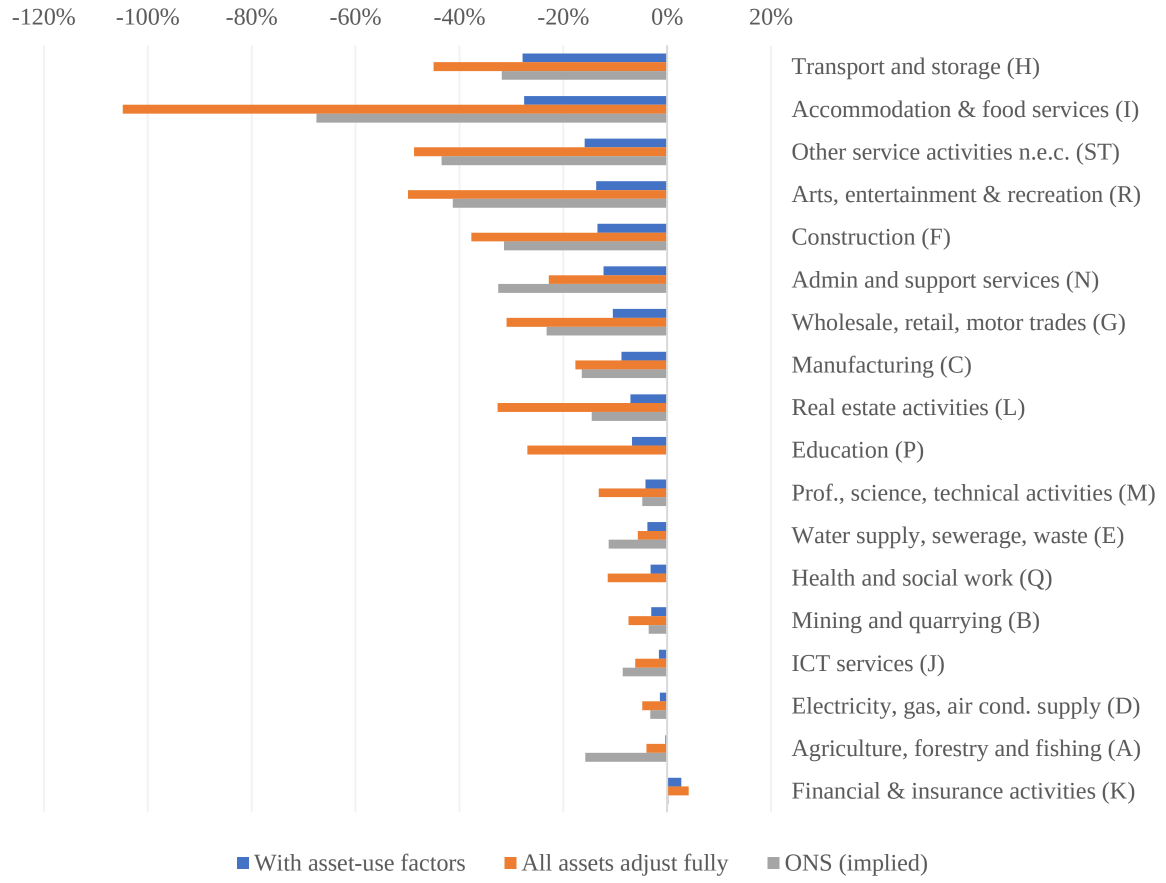
At the industry level, the impact of the factors is more significant, reflecting the differences in asset mix in each industry. Figure 7 shows the quarter-on-quarter change in capital utilisation in Q2 2020 by industry with asset-use factors, without factors (but still using the occupation-asset matching approach introduced in this paper), and the simple change in average hours worked (the approach used in the official MFP estimates from the ONS, as in ONS, 2021b, a simplified version of the BFK method). 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 ONS approach (simplified BFK) somewhere between. This reflects that the occupation-asset matching relies on detailed industry-by-occupation data from the LFS[16] 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

[16] A multi-purpose, household survey, not designed for this sort of detailed modelling work.

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 a simplified-BFK approach, quarter-on-quarter growth rate, Q2 2020



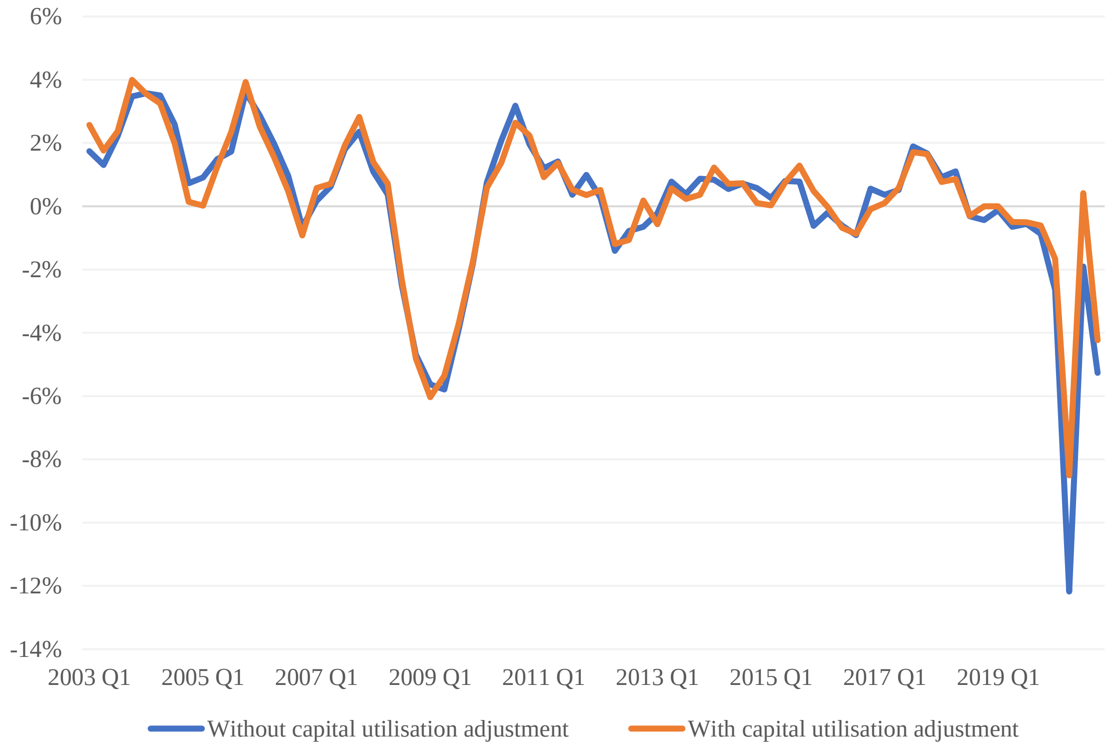
Source: UK Labour Force Survey, ONS, authors' calculations.
Notes: ONS data are implied from the difference between adjusted and unadjusted capital services data. No ONS estimate available for Education (P) or Health and social care (Q) due to suppressions. The ONS estimate for the finance industry (K) is zero. Data are in natural log changes, hence can be less than 100%.

5.4. 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 unadjusted MFP 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



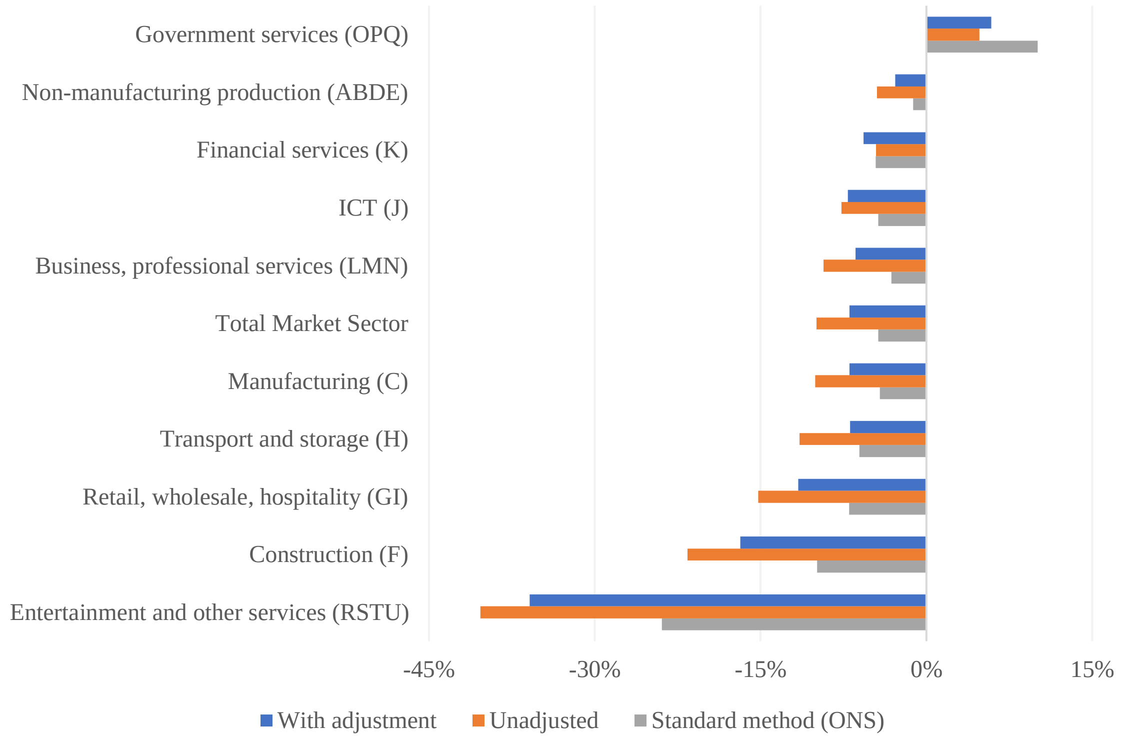
Source: UK Labour Force Survey, ONS, authors' calculations.

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, not adjusted for capital utilisation, adjusted with our central measure, and adjusted with the ONS approach (simplified BFK). 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 simple hours-methods (as used by the ONS), in line with the findings from Figure 7.

Correlations between output and MFP growth are weaker (i.e. MFP is less procyclical) when applying the capital utilisation adjustments than when not, in line with the literature, in almost[17] all industries. This is true for quarter-on-quarter and quarter-on-same-quarter-a-year-ago growth rates, with and without including the period of the coronavirus pandemic.

Figure 9 – Comparison of MFP quarter-on-quarter growth rates by industry. with and without a capital utilisation adjustment, and a simplified-BFK approach, Q2 2020



Source: UK Labour Force Survey, ONS, authors' calculations.

6. Discussion

We believe that our innovations to the more standard hours-based measures to adjust for capital utilisation (the BFK method) are conceptually well grounded, and should improve the validity of that method. In particular, we account for heterogeneity across industries and assets for the first time, addressing Denison's (1969) critique. The matching of occupations to assets is a conceptual enhancement on the existing literature, although the allocations would benefit from external review and could be further refined. The method does rely on a number of assumptions, which are currently not supported by sufficient evidence. However, in practice in this application, the results produced by this method are disappointing, and do not display key features that we would like them to.

[17] 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.

Aside from the conceptual advantages, there are some positives from these measures. We judge that the results covering the period of the coronavirus pandemic in 2020 are of a broadly sensible shape and magnitude. This is the period when an adjustment for variations in capital utilisation is arguably most necessary, so the fact that the method produces sensible results, both in the aggregate and by industry, is somewhat reassuring.

This method can also be estimated at quarterly frequency, and on the same timescales as official MFP estimates in the UK produced by the ONS, making it suitable for use in official statistics applications (see further discussion below). It will not be subject to revision over time that would be the same if using a filter of hours actually worked, and thus avoids the criticism of Kurmann and Sims (2021).

The main shortcoming is that the resultant estimates of capital utilisation do not match trends present in other sources, principally business surveys. While one should not cling too closely to one's priors, the estimates produced by this method do not 'feel right'. A major issue is the lack of a strong effect during the 2008/09 downturn, although this is present to a small degree in some industries. Another is that the series shows very little cyclical variation, such that the impact on MFP measures is minimal. That said, we are measuring an unobservable and difficult-to-measure variable, and we do not have a reliable benchmark to compare against. As such, we cannot be sure whether our results are any more or less accurate than others.

The reason for the lack of 2008/09 dip is that usual hours worked responded similarly to actual hours worked in most industries, meaning the ratio between the two, which drives our utilisation measure, is largely unchanged. We have argued that 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 unadjusted was problematic, and the adjustments we trialled made relatively little difference (see Figures A1 and A2 in Annex A for more details). We suspect further improvements to the 'baseline' would improve the estimates – using a longer window for the baseline (rather than the four quarters we used) might help.

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, averaged 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.

A further consideration is that lower utilisation of business capital might be offset by greater utilisation of non-business capital. For instance, the move to homeworking during the coronavirus pandemic clearly reduced the utilisation of business-owned buildings, but would have increased the utilisation of household-owned capital, especially dwellings (houses) as well as home furniture and ICT technology. Eberly, Haskel and Mizen (2022) term this "potential capital". This potential capital is not included in the capital input measures in standard productivity analysis, so an increase in its utilisation would not be accounted for. Accounting for a fall in utilisation of business-owned buildings during the coronavirus pandemic, but failing to account for the offsetting increase in utilisation of household-owned capital, would risk reversing the bias in measured MFP rather than eliminating it. The relatively low use-based deterioration factor we apply to buildings (see Table 2) might therefore be helpful in avoiding an overly strong effect of homeworking on total capital utilisation.

This paper was motivated by the coronavirus pandemic, which led to large and sharp movements in economic variables, including (as measured) MFP. Standard measures of capital services and MFP, such as those produced by national statistical institutes like the ONS in the UK, are not responsive to shocks in the short-term. Quarterly MFP measures in particular will be susceptible to variations in capital utilisation due to idiosyncratic factors. Implementing an adjustment for the change in capital utilisation may improve the usefulness of such measures. More thought should be given to whether, and how, national statistical institutes adjust their MFP measures for variations in capital utilisation – at all times, or just during economic shocks such as the coronavirus pandemic.

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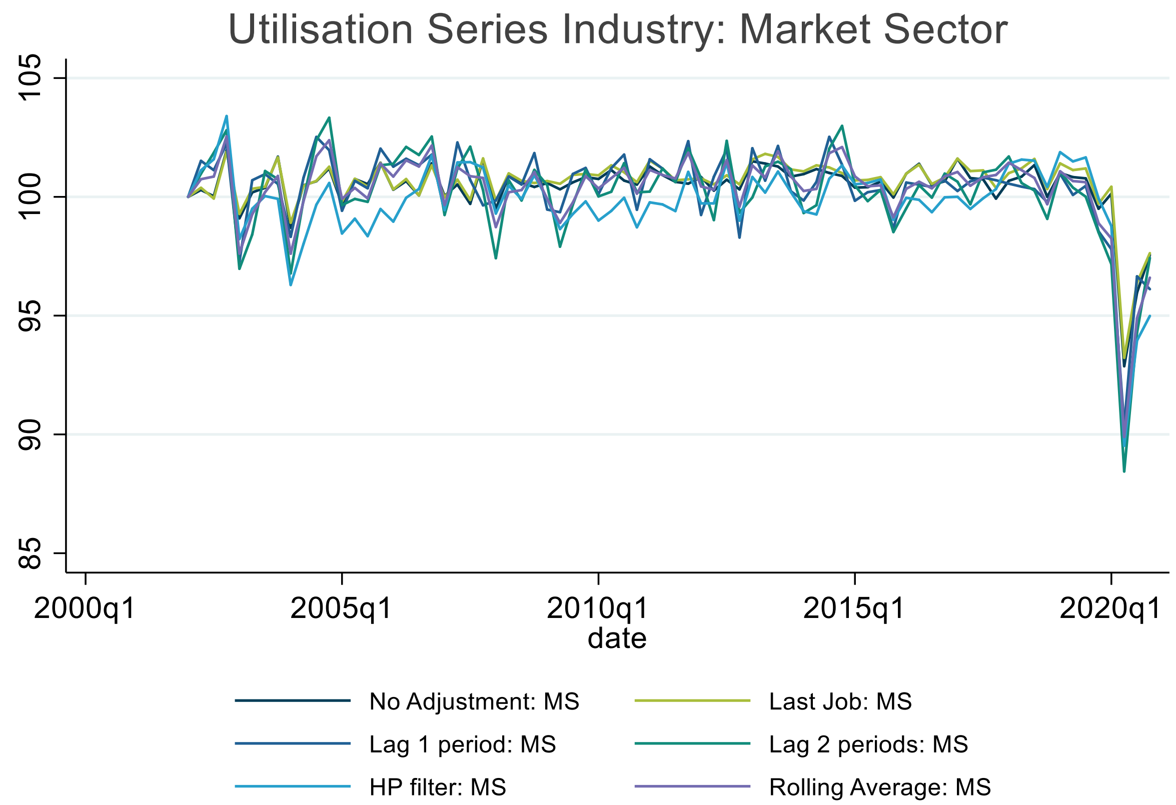
Annex A – Additional capital utilisation charts

Figure A1 – Capital utilisation series, with and without four-quarter baseline adjustment, UK market sector and manufacturing, Q1 2002 = 100, Q1 2002 to Q4 2020



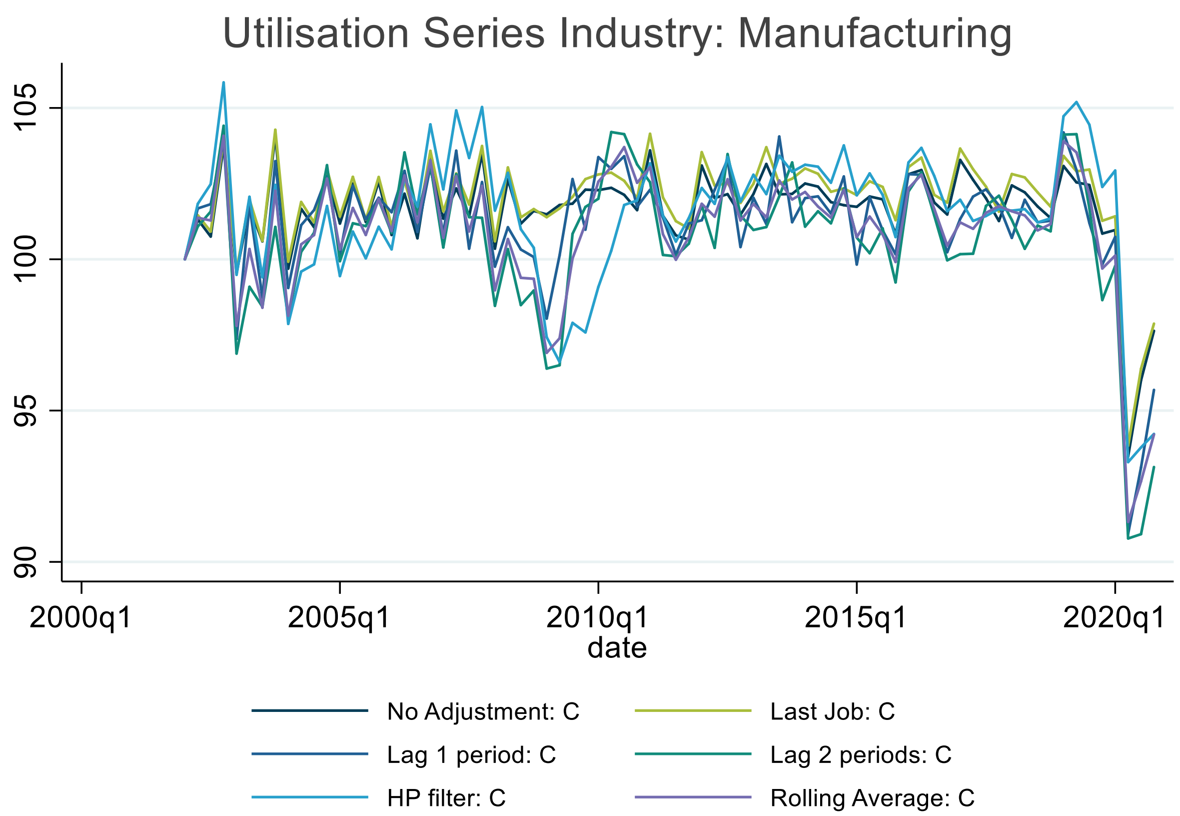
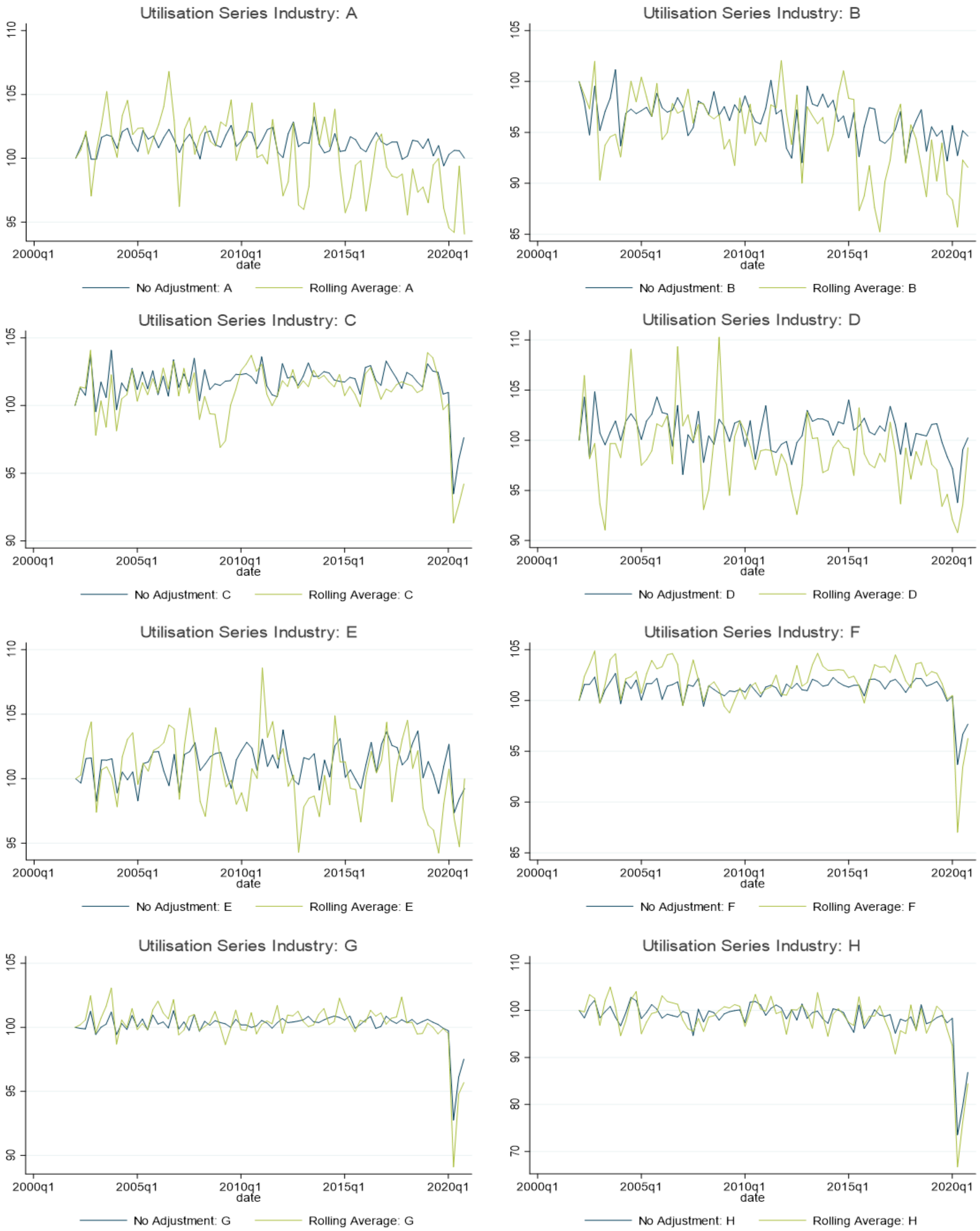
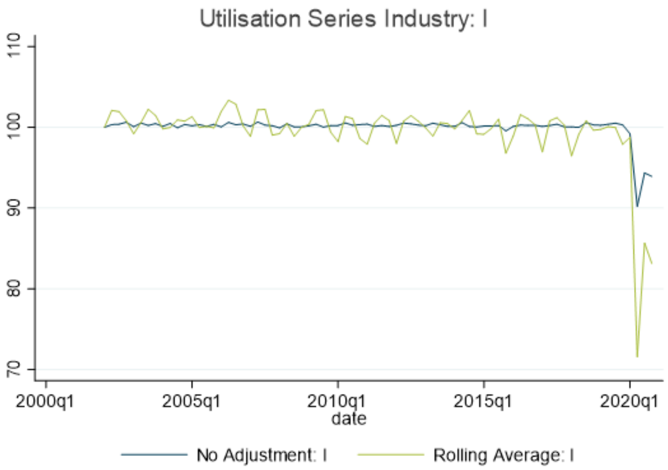
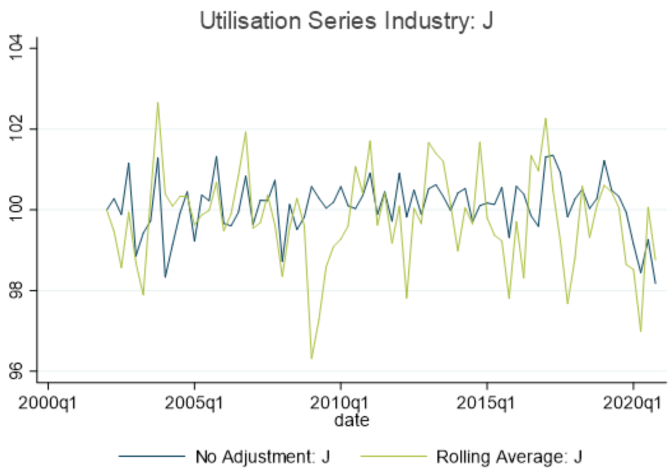
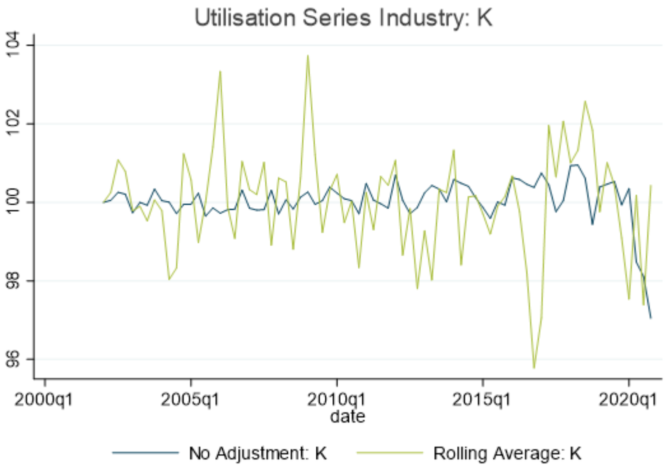


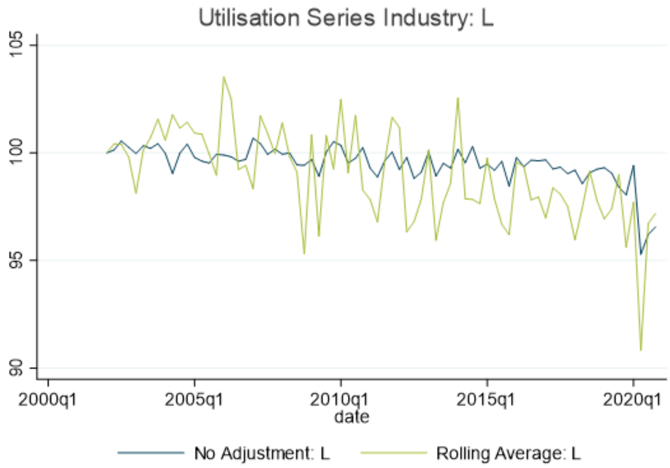
Figure A2 – Capital utilisation series, with and without four-quarter baseline adjustment, by industry, Q1 2002 = 100, Q1 2002 to Q4 2020 Q4

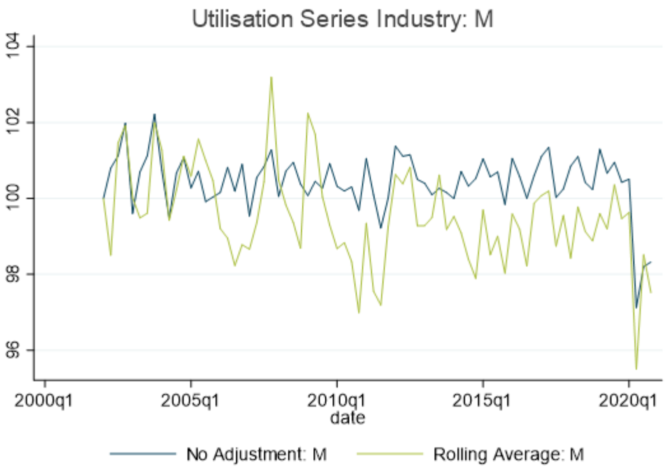


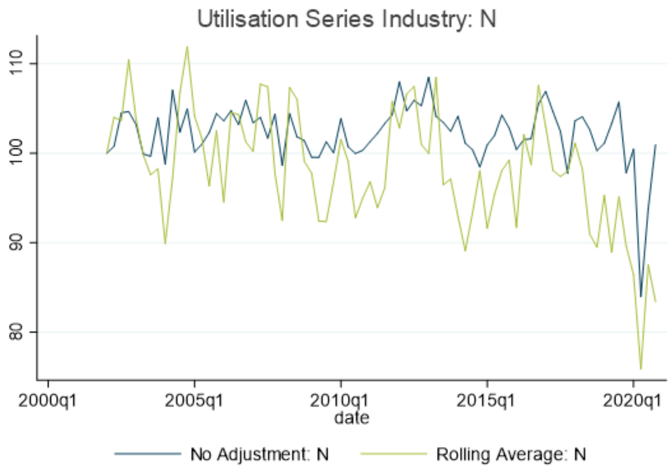

Utilisation Series Industry: I
70
80
90
100
110
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: I
Rolling Average: I

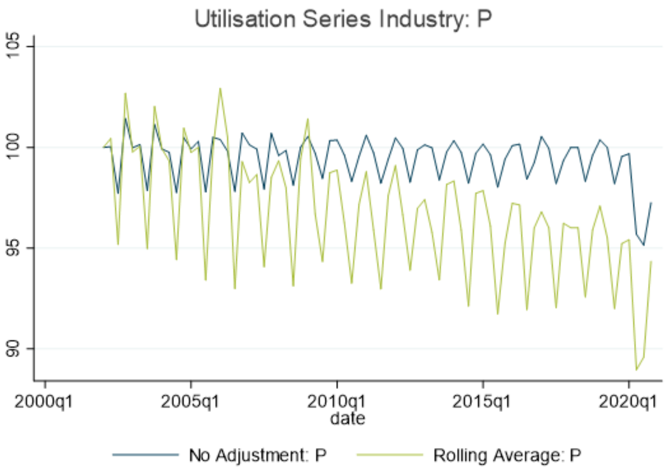

Utilisation Series Industry: J
96
98
100
102
104
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: J
Rolling Average: J

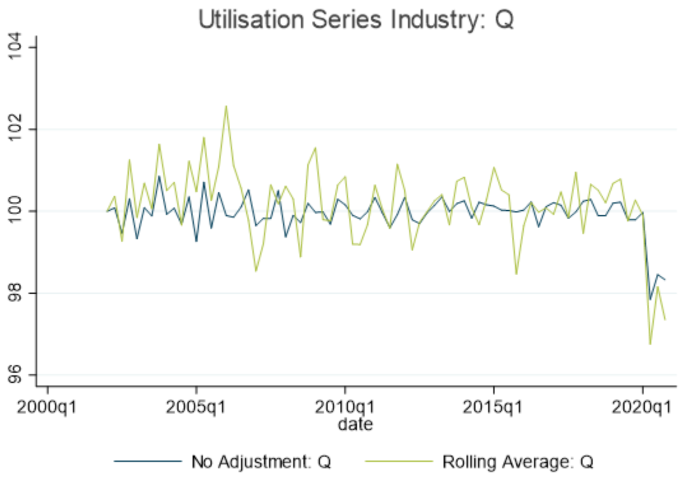

Utilisation Series Industry: K
96
98
100
102
104
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: K
Rolling Average: K

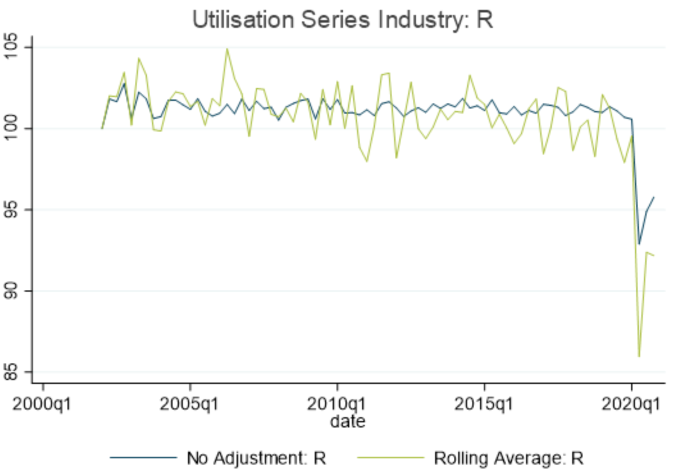

Utilisation Series Industry: L
90
95
100
105
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: L
Rolling Average: L

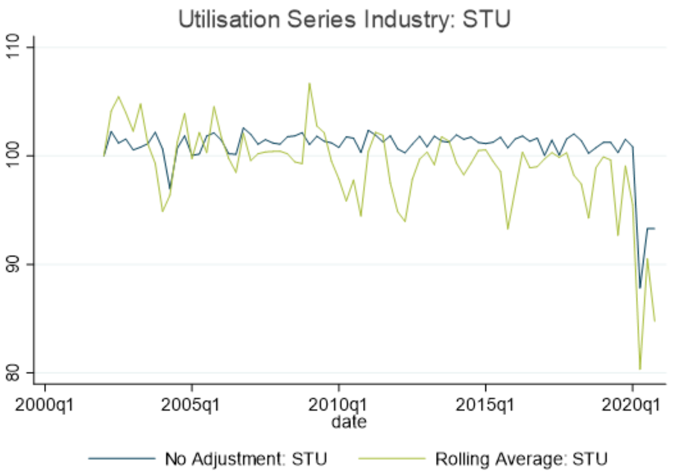

Utilisation Series Industry: M
96
98
100
102
104
2000q1
2005q1
2010q1
2015q1
2020q1
date
No Adjustment: M
Rolling Average: M


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 B – More details on the allocation of occupations to assets

Table B1 – Allocation of occupations to assets, by SOC 2010 code

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
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

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
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

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
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

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
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

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
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.

Process of matching occupations to assets

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 3.4 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

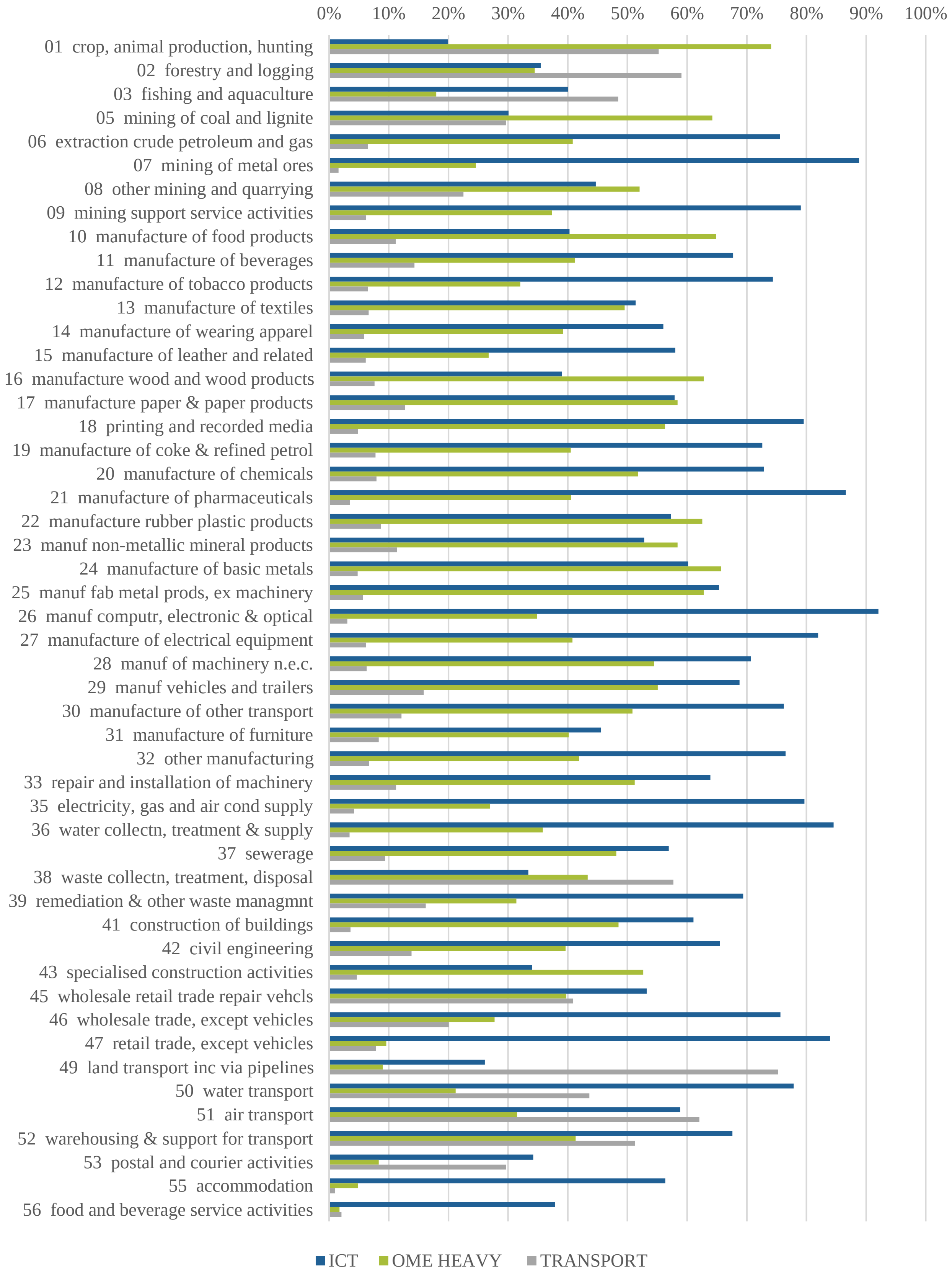
The matches to the asset classes are good, and the tasks and assets described for the level are all consistent with the assets in question.

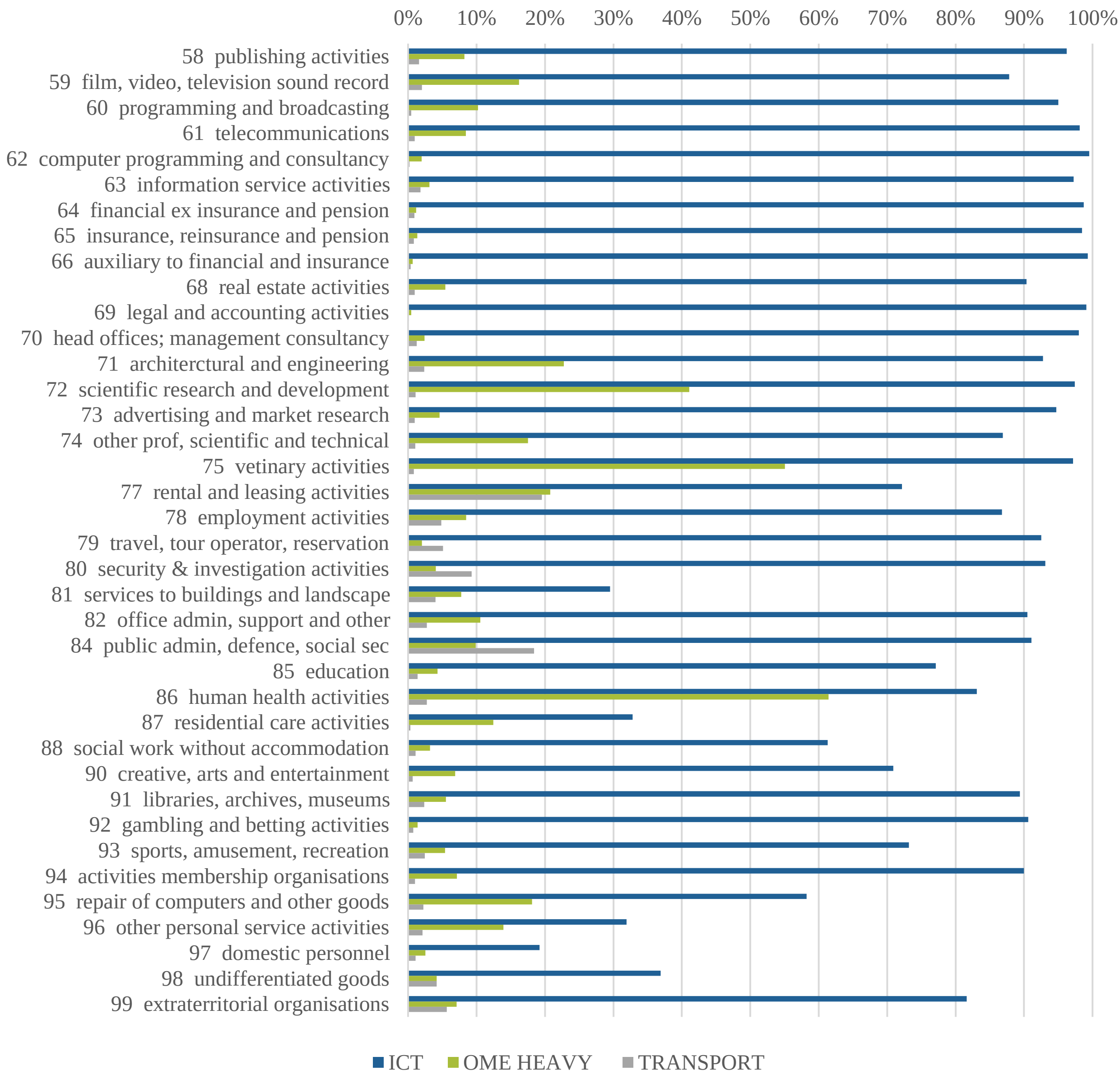
The O*NET data were matched from US to UK occupation codes, via the International Standard Occupation Classification (ISCO-08), using a series of publicly available conversion tables[18]. For each question (asset), we multiplied the level (intensity) by the importance to give a composite score.

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.

[18] The method is similar to that described in ONS (2022), although without the truncated proportional conversion matrices. Since this is only supporting information, we omit further details here.

Figure B1 – Proportion of hours worked in each occupation-asset group, by industry division





Note: The chart 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 do not total 100%.