

# Speech

# Will the pandemic "scar" the economy?

Remarks given by

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# 1. Introduction

Good morning everyone and thank you for having me here today. I'm delighted to be in Liverpool, albeit remotely, and very much hope to able to visit in person when the pandemic allows.

I'd like today to talk about my view on the more medium-term prospects for the economy, what economists, perhaps uninvitingly, call the supply side. The exam question is: has the pandemic damaged the feasible capacity of the economy? In his acclaimed book, the author Sebastian Mallaby called Alan Greenspan "The Man Who Knew". What was it that Mr Greenspan knew? Mallaby argues that Mr Greenspan was early to recognise that due to the IT revolution the US economy was capable of more productivity growth than others thought possible: that is, that the supply side was improving.<sup>1</sup>

I don't of course claim to have the clairvoyant powers of Mr Greenspan but I mention this as a motivation for why it might be important. In this speech, I'd like to make five main points:

- During the pandemic, investment, like in all recessions, has fallen. But that fall was concentrated in buildings and structures. Investment in intangibles, such as R&D and software, has stayed comparatively strong. This significantly reduces the risk of future scarring.
- 2) The prospect of a shift in the way we work through increased working from home and, perhaps more importantly, the acceleration of digitalisation offers further scope for supply-side optimism.
- 3) The labour market outlook has improved considerably in 2021 and the measures of labour market mismatch are falling.
- 4) The anticipation of improved supply brings demand forward now and might add to inflationary pressure.
- 5) In the immediate term, the risk of a pre-emptive monetary tightening curtailing the recovery continues to outweigh the risk of a temporary period of above-target inflation. For the foreseeable future, in my view, tight policy isn't the right policy.

<sup>&</sup>lt;sup>1</sup> Mallaby notes Mr. Greenspan relied on data by Fed staff, naming (p.493) Carol Corrado, whom I am fortunate to work with. Mallaby's account suggests Mr. Greenspan knew about a lot of other things (p.674-5) such as monetary policy and housing finance and the threat of lowflation but "the productivity call was most noted" (p.675). His criticism is that little was done about financial fragility.

# Figure 1: Bank of England GDP forecasts



# 2. Some facts and forecasts to be explained

**Figure 1** shows the path of the economy since 2017 and three forecasts. The solid line shows that quarterly GDP fell 22%, from a peak of 100 in 2019 Q4 to 78 in 2020 Q2, followed by a 19% recovery to a mini-peak of 93 in 2020 Q4. Thus an immediate lesson of the graph is to beware of soothsayers quoting gargantuan growth to grab headlines of record recoveries. When the economy is very low, almost any percentage rise is going to be very high.

The graph shows three forecasts. Three points are worth making here.

Firstly, comparisons of the dotted and dashed lines during the pandemic put into context the latest MPC forecast for the most likely evolution of output over the medium term. As you can see, the actual outturns in, say, the latter part of 2020 onwards, were stronger than we had forecast in February. One reason is that output was more robust to the tight restrictions placed on activity in 2021 Q1 than we had expected.

Secondly, we still have some way to go to get back to the pre-pandemic level of 2019 Q4. The May 2021 *MPR* forecasted a return to that level by the end of the year, which would represent a mighty achievement but nevertheless is still two years without economic growth.

Third, and the main subject of this talk, in the medium term **Figure 1** shows that by the end of the May 2021 *MPR* forecast, the UK economy was not expected to catch up with the path published in the January 2020 *MPR*. This shortfall is "scarring". What causes it and how much is it likely to be?

# 3. Scarring and output

I discussed the channels behind scarring in a speech in March (Haskel, 2021) and recapitulate and extend that discussion here.

# 3a. Understanding economic output

Output in the economy equals output per hour times the number of hours worked.

$$Y = \frac{Y}{H}H$$
 (1)

Output per hour is productivity. The number of hours worked is the obverse of participation in the labour market and unemployment. So this is a neat split of the economy into factors affecting productivity and the labour market. And we may think of scarring as occurring if productivity and/or hours worked are lower than previously expected. So what determines productivity and hours and why might they deteriorate?

# i. Productivity

One factor that affects productivity is the composition of the economy. At the risk of complicating the notation we can capture this by considering Y/H as the productivity of each industry, weighted by the share of that industry in total hours

$$Y = \left(\sum_{i} \left(\frac{Y}{H}\right)_{i} \left(\frac{H_{i}}{H}\right)\right) H$$
(2)

What then determines productivity in each industry? Output per hour in each industry depends on input per hour and the efficiency with which they are used. There are three key inputs. Human capital, denoted below by L, is a measure of education, skills and training; tangible capital K is the stock of machines, buildings and vehicles; while intangible capital R is the stock of paid-for knowledge (lines of computer code, drug formulae discovered by R&D, design blueprints, know-how in running supply chains). We may divide the "efficiency of operation" into two parts. One is the intensity with which inputs are used, Z, a somewhat short-term effect: overtime for example. The second is the state of generally available knowledge enabling inputs to be used better, A (also called Total Factor Productivity (TFP)): most airlines now use speedy boarding for example. Finally, economic theory suggests that under certain conditions, the inputs' private contributions to the output produced per hour depend on their share of total costs,  $s_i$  This gives

$$\left(\frac{Y}{H}\right)_{i} = A_{i} \left(\frac{L}{H}\right)_{i}^{S_{L_{i}}} \left(\frac{K}{H}\right)_{i}^{S_{k_{i}}} \left(\frac{R}{H}\right)_{i}^{S_{R_{i}}} Z_{i}$$

$$\tag{3}$$

# ii. Hours

Turning to hours, we may write equation 4 which shows hours H are driven by the proportion of the population (POP) participating in the labour force (LF), the employment rate, N/LF where N are the numbers in employment and the average number of hours (H/N) they work.

$$H = POP * \frac{LF}{POP} * \frac{N}{LF} * \frac{H}{N}$$
(4)

In usual times the labour force consists of people in employment plus those willing to work, but unemployed: LF=N+U. With a furlough scheme<sup>2</sup> in operation, let us define LF=N<sup>NF</sup>+U+F where N<sup>NF</sup> are those in employment but not-furloughed workers and those furloughed working at a second job, that is reflected in H, giving

$$H = POP * PART * (1 - u - f) * H/N^{NF}$$
(5)

Where PART is the labour-force participation rate and the last term is average hours per non-furloughed worker (which changes if furloughed workers are working a job besides their furlough).

# 3b. Scarring and economic output

Combining all this gives an expression for the level of output

$$Y = \left(\sum_{i} A_{i} \left(\frac{L}{H}\right)_{i}^{S_{L_{i}}} \left(\frac{K}{H}\right)_{i}^{S_{K_{i}}} \left(\frac{R}{H}\right)_{i}^{S_{R_{i}}} Z_{i} \left(\frac{H_{i}}{H}\right)\right) POP * PART * (1 - u - f) * H/N^{NF}$$

$$\tag{6}$$

We can define scarring as a situation whereby expected Y deviates from some counter-factual output, say the output that would have prevailed had the pandemic never occurred. We set f = 0 as the furlough scheme ends. Thus we write, subscripting counter-factual output by 0,

$$\frac{Y}{Y_{0}} = \frac{\left(\sum_{i} A_{i} \left(\frac{L}{H}\right)_{i}^{S_{L}i} \left(\frac{K}{H}\right)_{i}^{S_{k}i} \left(\frac{R}{H}\right)_{i}^{S_{R}i} Z_{i} \left(\frac{H_{i}}{H}\right)\right) POP * PART * (1 - u) * H/N}{\left(A_{0} \left(\frac{L_{0}}{H_{0}}\right)^{S_{L}} \left(\frac{K_{0}}{H_{0}}\right)^{S_{R}} Z_{0} \left(\frac{H_{i}}{H}\right)_{0}\right) * POP_{0} * PART_{0} * (1 - u_{0}) * H/N_{0}}$$
(7)

where in the final terms of the numerator we suppose the furlough scheme is over.

# 3c. Calculating scarring

To compute post-pandemic scarring in, say three years' time, we need to forecast the various terms in (7) over the next three years and compare their level to a counterfactual. That counterfactual we take to be the forecast for the economy pre-pandemic. Consider now the various terms.

<sup>&</sup>lt;sup>2</sup> I define both the CJRS (employees) and SEISS (self-employed) as the furlough scheme.

First, the capital terms follow mechanically from the observation that capital is formed through investment *I*x net of depreciation at rate  $\delta_x$  such that:

$$x_t = (1 - \delta_x) x_{t-1} + I x_t$$
(8)

where x is one of {K,R}. Thus to forecast future K and R relative to pre-pandemic, we apply the above equation using actual investment in 2020 and forecast investment to 2024.

Second, we need to forecast A. The state of public knowledge depends at least in part on firms learning from other firms. For example, within about 18 months of the iPhone appearing, almost all smartphones looked just like it (gone were pull-out aerials, fold-down speakers and physical keyboards). The iPhone design spilled over to other firms.

Theory and evidence suggests these "spillovers" effects are important and come from the sharing of intangible knowledge. Over the last 50 years the level of UK productivity has increased by 150 percent, of which investment in private capital accounts for slightly less than half, suggesting that knowledge spillovers are important. Now, tangible investments have a relatively straightforward mapping to productivity. Machines can do things faster and more accurately than humans so labour productivity increases when a worker is paired with a machine. Some intangible investments also have this straightforward interpretation. For example machines are faster and more accurate when paired with better software and some intangible investments, like research and development directly feed into innovations. But a key difference is that tangible investments, like machines, are only used by the firms that own them, whereas intangible investments, like design in the iPhone example, can be used by others. Thus intangibles are also likely to generate positive spillovers as knowledge, ideas and best practices spread throughout the economy. That is, the social return from these investments is greater than the private return. In economic data this would manifest as higher aggregate TFP.

Of course, some intangibles, such as patented medicines, will not spill over to others directly since they have intellectual property rights attached to them. But an extensive academic literature suggests an internal elasticity of intangible investment on productivity growth of 0.1 and an external elasticity of 0.2 (the internal elasticity captures the responsiveness of productivity to the industry's own intangible investments while the external elasticity refers to the response to other industries' intangible investments). All this suggests modelling A as depending on intangibles and the state of general knowledge T (e.g. publically funded science, or open source software):

$$A_i = T_i(R)_i^{\gamma_i} \tag{9}$$

where gamma captures the elasticity of TFP to the stock of intangible capital.

Third, if we are doing longer-term projections, we might assume that Z=1 and  $H_i/H$  is unchanged.<sup>3</sup> So we can rewrite (7) as

$$\frac{Y}{Y_{0}} = \frac{\left(\sum_{i} T_{i}(R)_{i}^{\gamma_{i}} \left(\frac{L}{H}\right)_{i}^{S_{L_{i}}} \left(\frac{K}{H}\right)_{i}^{S_{k_{i}}} \left(\frac{R}{H}\right)_{i}^{S_{k_{i}}} \left(\frac{H_{i}}{H}\right)_{0}\right) POP * PART * (1 - u) * H/N}{\left(A_{0} \left(\frac{L_{0}}{H_{0}}\right)^{S_{L}} \left(\frac{K_{0}}{H_{0}}\right)^{S_{k}} \left(\frac{R_{0}}{H_{0}}\right)^{S_{R}} \left(\frac{H_{i}}{H}\right)_{0}\right) * POP_{0} * PART_{0} * (1 - u_{0}) * H/N_{0}}$$
(10)

We are now in a position to review the sources of scarring. Medium-term output will be below that previously projected if:

- a. On the productivity side, there is damage to inputs, such as skills (L) and capital (K and R). Notice that intangible capital R has a double effect, on both the inputs within the firm and outside the firm as well via spillovers.
- b. On the labour market side, population, the participation rate (PART) or average hours (H/N) has fallen, or the unemployment rate (u) has risen.

Against this, the framework suggests there might be some sources of higher than expected output (Y greater than Y0):

- a. Working from home might raise PART (e.g. current child care providers with school-age children currently not working can now work from home during school hours).
- b. The digitisation of retail and health might raise K and/or R in those sectors and so raise productivity.

All this suggests the extent of scarring is an empirical matter. We go on to discuss this next.

# 4. Output losses during the pandemic

# 4a. Output, productivity and hours over the pandemic

Based on equations (1) and (5), **Table 1** decomposes the fall in output over the pandemic, to date, into the productivity and hours effects and their subcomponents.

<sup>&</sup>lt;sup>3</sup> One might argue that there will persistent changes in industrial structure. See Saunders (2021).

Relative to 2019q4 levels		Productivity			Hours					Мето			
	Output	Total	Within	Reallocation	Total (H)	Population aged 16+ (POP)	Participation rate = LF/POP (PART)	Employment share of labour force	Average hours (H/N)	Unemployment rate, % (u)	Furlough* share of labour force (f)	Employment share excl. furlough	Average hours excl. furlough
Column	0 (1*2)	1 (1a*1b)	1a	1b	2 (2a*2b*2c*2d) or (2a*2b*5*6)	2a	2b	2c	2d	3	4	5 (2c-4)	6 ( (2 / (2a*2b*5))
2019 Q4	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	3.8	0.0	1.00	1.00
2020 Q1	0.97	0.99	0.98	1.01	0.98	1.00	1.00	1.00	0.98	4.0	2.1	0.98	1.00
2020 Q2	0.78	0.97	0.89	1.09	0.80	1.00	0.99	1.00	0.81	4.1	30.4	0.68	1.18
2020 Q3	0.91	1.04	1.03	1.00	0.88	1.00	0.99	0.99	0.89	4.8	12.4	0.86	1.03
2020 Q4	0.93	0.99	0.97	1.02	0.93	1.01	0.99	0.99	0.95	5.1	9.9	0.88	1.06
2021 Q1	0.91	1.00	0.98	1.03	0.91	1.01	0.99	0.99	0.92	4.8	14.1	0.84	1.08

### Source: ONS, HMRC & author calculations

Note: The within and reallocation productivity effects are derived from comparing total productivity to an industry hours weighted average of productivity holding hours shares fixed at the observed level of 2019Q4.

\* I define the furlough share as the full-time equivalent furlough divided by the labour force. Those on furlough consist of CJRS (employees) and SEISS (self-employed). In calculating full-time equivalent (FTE) furlough, I assume full-time furloughed work zero hours while those on flexi-furlough and the SEISS work 50% of their usual hours. This simplifying calculation may overstate the Furlough share in column 4 as fully furloughed workers may have a second job and therefore work some hours, or those on flexi-furlough or the SEISS work less than 50% of their usual hours; and the majority of those furloughed have come from sectors with a lower average hours than the whole economy average. See appendix for further details on the issues combining data from the LFS and job support schemes. LFS data as at 9<sup>th</sup> July 2021,

The table shows that in 2021Q1 output was still 9% lower than 2019Q4 levels. What are the proximate causes of this fall?

Column 2 shows that the 9% loss of output can be entirely accounted for by hours worked, not productivity. That is because there has been a fall in within-firm productivity of 2% (column 1a), but this has been offset by increased across-sector productivity (column 1b), as the partial closure of the less productive, pandemic-hit, sectors (such as restaurants) mechanically lifted measured productivity (so-called "batting average" effects).

The panel from column 2 onwards decomposes the 9% fall in total hours.<sup>4</sup> Recall that we may write the decomposition of hours worked as;

(H = POP \* PART \* (1 - u) \* H/N) or  $H = POP * PART * (1 - u - f) * H/N^{NF})$ .

We can see from **Table 1** that, based on the left-hand equation, the total hours fall is almost entirely accounted for by the decline in the average number of hours worked per worker – H/N (this includes those who are working and those on a furlough scheme). We also see, via the right-hand equation, that the decline in average hours is

<sup>&</sup>lt;sup>4</sup> The population figures for 2020 and 2021 in column 2a are based on pre-pandemic trends. New population <u>data</u> released in July 2021 suggest that by 2020 Q4, the UK's population relevant to weighting the LFS had grown to 53.5 million – a 0.2% annual increase from 2019 Q4, the slowest rate of increase since the early 1990s. Employment in the ONS Labour Force Survey (LFS) are calculated by scaling the percentage of employees derived from survey responses to the size of the UK population, so employment may be revised down if the population are revised down. However, this should not materially affect the proportions in the LFS, since both the numerator and denominator are affected. As such the ratios in columns 2b, 2c, 3, 4, 5 and 6 should be largely unaffected.

driven those on various types of furlough, who predominantly come from industries with lower average hours worked per worker. This decline more than offsets the higher average hours worked per non-furloughed worker in column 6<sup>5</sup> leading to the overall decline in average hours seen in column 2d.

# What about unemployment?

As the table shows, from a trough of 3.8% in 2019 Q4, the unemployment rate peaked at 5.1% in 2020 Q4, and came back down to 4.8% in 2021 Q1. The peak unemployment rate seen is some way below that implied by a standard Okun coefficient given the collapse in GDP last year. GDP troughed 25% below pre-pandemic levels which, with a standard Okun coefficient of 0.4, implies the unemployment rate should have peaked at around 14%.

There are two main reasons for this. The first is that the government's furlough scheme, now scheduled to end in late September, has kept workers in the official employment statistics rather than made them swell the ranks of the unemployed. At its peak during the first wave of the pandemic, an estimated 30% of the labour force were furloughed (column 4), equivalent to close to 11 million jobs. The second is an increase in the number of people not actively looking for work and therefore counted as not in the labour force. The labour force participation rate (column 2b) has fallen slightly since the onset of the pandemic as the lockdowns made it hard to look for work. The key take-away from **Table 1** is that total hours have sharply decline because hours per worker have fallen. In turn, that is due to a rise in the furlough rate – where workers are working zero hours (or fewer hours than usual if on flexi furlough) – that has offset a rise in the average hours per employed worker. Thus the critical question for the future is what will happen to the employment prospects of those furloughed workers. I return to this below.

# 4b. Investment and capital over the pandemic

We now turn to the more medium-term considerations.

To compute the outlook for capital, we start with changes in the stock of different types of capital during the most recent period.<sup>6</sup>

Capital accumulates with investment as in equation (8). **Table 2**, final row, shows that overall business investment fell by a massive 12% in 2020. As a result the business capital stock barely grew: 0.1% against the pre-pandemic growth of 1.7% (column 3). Therefore relative to its pre-pandemic trend, the capital stock is now lower than it otherwise would have been, potentially reducing the productive capacity of the economy.

<sup>&</sup>lt;sup>5</sup> As per the footnote under Table 1, I abstract from those fully furloughed workers who can take up a second job.

<sup>&</sup>lt;sup>6</sup> I focus on business investment and capital.

Asset	Change in Investment (1)	Change in capital stock (2)	Pre-pandemic growth of capital stock (3)	Share of capital stock (4)	Share of capital services (5)
Buildings	-11.5%	1.2%	1.4%	37%	32%
Intangibles	1.6%	2.2%	2.7%	12%	19%
Tangible	-21.9%	-1.1%	1.7%	51%	49%
Total	-12.2%	0.1%	1.7%	100%	100%

# Table 2: Investment and capital formation by asset, 2019Q4 to 2020Q4

Source: ONS experimental productivity estimates

Note: Column (1) is the calendar-year change in real chain-weighted gross fixed capital formation between 2019 and 2020. Column (2) is the change in the capital stock between 2019Q4 and 2020Q4. Column (3) is the average annualised growth rate of the capital stock over the period 2014Q4-2019Q4. Column (4) is the asset share in the measured capital stock. Column (5) is the asset share in measured capital services, the estimated share of capital income accruing to the asset. Intangible assets are capitalised research and development, software, databases and artistic originals. Tangible assets are other structures, machinery, and equipment.

But there is an additional important message of **Table 2** summarised in **Figure 2** showing the sharp difference in the type of investment. As the figure shows, Intellectual Property Products investment has held up whereas investment in other assets has declined.

# Figure 2: Business investment components



More detail on this is set out in **Table 2**, where the first three rows break out the capital stock and investment into three types of assets: buildings; tangible capital excluding buildings (i.e. plant and machinery including computers, structures and vehicles), and intangible capital (e.g. intellectual property). Column 1 shows the fall in investment in 2020 was concentrated in tangible capital and buildings, whereas intangible investment held up. The resilience of intangible investment over the pandemic should help mitigate scarring, thanks to the spillover effects I described above. In addition, as column 2 shows the fall of investment in buildings has not resulted in the commercial buildings capital stock falling far below trend (the stock of buildings is so large that a pause in

investment for a relative short time has a small effect). Further, as discussed below, production has switched locations from commercial premises to dwellings.

# 4c. Scarring: output losses over the medium term

Scarring from capital and spillover channels arises from this lower investment in 2020 and in the next few years, which changes capital stocks mechanically via equation 8. Thus to calculate scarring I have to forecast investment by asset type. I do this by relying on the latest (May 2021) Bank of England forecast for *all* investment (there is no forecast by asset type) and then make assumptions about what share of aggregate investment accrues to what asset types over the forecast period.

The resulting scarring assumptions, set out in **Table 3**, turn out to be sensitive to the choice of these shares and the table shows some upper and lower bounds. For example, the contributions of R and spillovers from R have an upper bound of +0.6 and +2.1 respectively. These correspond to the assumption that the share of intangible investment stays high, as it was in 2020, in which case spillovers are enough to eliminate scarring and actually raise the level of output by 2024Q2. This scenario is in line with a story of a digitisation revolution on the back of the pandemic. Nonetheless it is worth noting that this high intangibles investment scenario would be a considerable departure from historical precedent.<sup>7</sup>

However if the share of investment tilts more towards its historic norms, as it might given the incentives of the government's super deduction scheme which encourages investment in plant and machinery, then there is scarring, with lower bounds of -0.2 and -0.7 as the table shows. This is because the intangible capital stock depreciates faster than other asset types and also contributes to scarring through the spillovers channel.

Component	Contribution by 2024
Human Capital (L)	[-0.3,-0.1]
Intangible Capital (R)	[-0.2,0.6]
Tangible Capital (K)	[-1.4,-0.3]
A: Spillovers from R	[-0.7,2.1]
Potential output (Y)	[-1.5,1.5]

# Table 3: Productivity scarring

Source: Author's calculations.

Note: Sets out the contribution of different channels to the change in potential output by 2024Q2. The exercise conditions on the business investment forecast embedded in the January 2020 and May 2021 Bank of England forecasts. The capital channels multiply the change in capital stocks by each assets share of capital income  $s_i$ . and overall capital share  $\alpha$  assumed to be a third. Capital stocks are built up using

<sup>&</sup>lt;sup>7</sup> We should note that in the most recent data (2021 Q1), IPP investment has fallen substantially, though the number is subject to greater uncertainty than usual and large revisions. The same pattern was observed last year but subsequently revised away.

a perpetual inventory method with annualised deprecation factors of (0.05, 0.10, 0.30) respectively for buildings, tangible and intangible assets. The spillovers coefficient is applied in a range of [0.1 to 0.2] based on Corrado et al (2017). For more details see the appendix.

The rest of **Table 3** sets out some other potential scarring contributions. The human capital channel (L) arises from lost-on-the-job experience during the pandemic. This can be approximated by taking the lost hours worked relative to a pre-pandemic forecast<sup>8</sup> and multiplying those lost hours by an experience coefficient. A reasonable estimate of this coefficient is the average value of an extra year's experience on the job in terms of wages. This has been estimated to be in a range of 1-3 percent (e.g. Buhai et al, 2014), which is also a range consistent with what one would get using the UK's Labour Force Survey. This coefficient would imply a year's lost experience ultimately would lower productivity via human capital by 1-3 percent.<sup>9</sup>

The contribution of tangible capital is negative; that is, the decline in tangible capital detracts from output whether tangible capital recovers or not. One source of uncertainty is the contribution of the commercial buildings capital stock as some of the decline in commercial buildings will likely be offset by the greater use of the domestic buildings capital stock through more working from home. We have assumed here that commercial buildings are unlikely to contribute to scarring although these calculations are not sensitive to that assumption (see Table A1 in the appendix).

Overall, I consider a scarring number in the range of -1.5 to 1.5 percent to be a reasonable estimate. This encapsulates the numbers from the Bank of England's latest May *MPR*, which estimated scarring along similar channels of about 1.25 percent. With a mid-point of 0% scarring, it paints a more sanguine picture than the May *Report*. By comparison, the OBR published a more pessimistic central scarring estimate of 3.0 percent back in March 2021, split evenly between lower capital, TFP, and labour supply.

The broader point is that the overall scarring range arrived at in **Table 3** is not just small considering the magnitude of the contraction experienced in 2020; it points to the possibilities of no scarring at all and even a boost to potential output relative to pre-pandemic. Of course, these calculations rely on all manner of assumptions. But the comparatively low numbers are founded on the observation that the pandemic has been combatted not only by the vaccines but also highly accommodating fiscal and monetary policy. Had there been no such response, it seems highly likely that scarring would have been much worse.

# 5. Quantifying scarring: discussion

We discuss now a number of further issues.

<sup>&</sup>lt;sup>8</sup> We use the January 2020 Bank of England MPR forecast as our baseline

<sup>&</sup>lt;sup>9</sup> Losses in schooling years during the pandemic will show up as future losses in human capital.

# 5a. Working from home

Let's start with remote working. The Decision Makers Panel survey suggests a shift to a hybrid model where working from home accounts for about 20% of hours worked post-pandemic, a rise from 7% pre-pandemic. What are the implications for the capital stock, productivity, and the supply of labour if this comes to pass?

It is helpful to draw a distinction between the capital *stock* – the accumulated assets that grow with investments and shrink with retirements and disposals – and capital *services*, the flow of services derived from the *productive* capital stock that enters formula (3).

How does that relate to home-working? The capital *stock* has not changed: commercial and residential buildings have not been demolished by the pandemic. What has changed is the structure of capital *services*. Levels of working from home have remained elevated throughout the pandemic, with peaks of almost half of working adults working remotely. This domestic capital allowed us to substitute the capital services of the desk, computer and internet connection we use in the office for a desk, computer and internet connection at home. The use of such "potential capital", effectively turning domestic dwellings into commercially productive capital has allowed us to keep the flow of capital services from buildings largely constant throughout the crisis, in those sectors of the economy where working from home has been possible (Eberly, Haskel, Mizen, 2021).

As well as massive substitution between commercial and domestic buildings, there has been a massive reduction in investment in commercial buildings. Such a falloff in investment would be indicative of future scarring had the potential capital of domestic buildings been unavailable. But the use of such "potential capital" suggests this is potentially a minor effect. It also suggests that in measuring the capital services in the economy, we should allow for domestic capital (many, although not all, current measures consistent only of business capital services).

If working from home has swapped one type of capital for another, how might it affect productivity? Equation 6 suggests at least one effect: if working from home was intrinsically more productive and hours shifted towards more home-working, then productivity levels will rise. What do we know about this?

First, many assume that working from home must be more productive since people don't have to commute, but this is mistaken. Not commuting might relieve stress and create more hours but that is not more productive in a GDP-per-hour-worked sense: instead it is a reallocation of non-work time from commuting to some other activity. Second, working from home is of course concentrated in a few sectors: it is impossible for service activities such as hotels, petrol stations and on-premises food and drink.

Third, of those who can work from home, the findings on relative productivity are very mixed. In an oft-cited study of China call-centre workers who were randomly assigned to work from home, the Stanford researcher Nick Bloom and his colleagues (2015) found workers' productivity rose quite substantially, by 13%.<sup>10</sup> Another

<sup>&</sup>lt;sup>10</sup> It is worth noting that the workers in the experiment were a selected group: they had to have a fast internet connection, spare room and no children at home.

(quasi) randomised study, of patent examiners, found their productivity fell after working from home, with more errors and more re-examination needed.

So what can we conclude? My interpretation starts with the observation that jobs are a bundle of tasks. A job which consists of a relatively small number of routine tasks - answering the phone and dealing with routine inquiries for example – is likely to be just as productive at home. Other jobs, which consist of a bundle of interrelated tasks – answering the phone, attending meetings, interacting with other employees – are likely less productive at home given the current difficulty of duplicating all aspects of human interaction electronically. For those less routine jobs, working from home is still likely less productive, although the fact that the output losses from successive lockdowns have got lower is consistent with an improvement in the relative productivity disadvantage of working from home. That relative improvement is likely to continue especially if other circumstances change (having schools open for example). Of course, whether more labour is working from home as the relative productivity of home-working rises depends on the ability to substitute work between home and work premises. If workers are more productive at home then a given output level requires fewer of them, which means less working from home. But if it is easier to substitute activity to home, then there is more working from home. Along with the observation that any positive productivity effects from home-working requires more investment in intangibles, to address the lack of the serendipitous interactions that take place in the office, I am doubtful of a strong productivity rebound from simply more working from home, but rather from the turn to a different form of activities such as digitalisation (see below).

Finally, working from home could increase labour-force participation, for example if more widespread remote working brought down barriers to work, such as lack of mobility or geographical distance. This could encourage people with disabilities, older workers and workers with caring responsibilities to participate in the labour force, increasing the supply of labour in the economy. I discuss participation more below.

# 5b. Digitalisation

**Figure 2** suggests a recent acceleration of digitalisation and automation/AI. The pandemic has acted as a strong incentive to reduce in-person contact. As **Figure 2** suggests, the successive lockdowns have accelerated the digitalisation of exchange between customers and businesses (e-commerce, interactive digital fitness), and between businesses (cloud-based transactions and service provision). And home-working has increased the business use of online technologies (video and communications technologies; cloud-based identity verification technologies).

# Figure 2: Digitalisation and automation during Covid-19



Source: McKinsey Global Business Executive Survey, July 2020, taken from IMF (2021).

Such an acceleration could be sustained especially in health care, where, for example, NHSX in the UK is moving towards much more remote monitoring of patients with routine diseases for whom visiting hospital is highly inefficient.

How does this fit in with the above? Digitalisation is a mix of tangible and intangible investment. For example, a pulse oximeter is a small electronic device that clips onto a patient's finger measuring pulse and blood oxygen. Used at home and linked to an app which it sends data to clinician who can then send back advice.<sup>11</sup> The sensor and comms equipment is tangible investment, the software that digitises information intangible investment. This could potentially raise productivity.<sup>12</sup>

# 5c. The labour market

I discuss participation and mismatch. As we saw in **Table 1**, the key is what happens to currently furloughed workers.

i. Participation

Labour force participation is difficult to forecast, having fluctuated quite a bit in recent years. After reaching a series high in February 2020, it has since fallen by over a percentage point and concerns exist around the degree to which it will recover following the pandemic. Much of these concerns relate to the over 50s group that account for about a quarter of the decline in activity<sup>13</sup> and around a fifth of those on furlough at the end of May. Two questions arise. Will those who moved to inactivity return to the labour force? And to what extent will those

<sup>&</sup>lt;sup>11</sup> See https://www.nhsx.nhs.uk/blogs/digital-home-care-for-people-with-coronavirus/, https://www.england.nhs.uk/blog/a-simple-device-hasbeen-a-lifeline-during-the-pandemic-and-could-change-how-we-provide-care-for-good/ and https://issuu.com/juliecrompton/docs/january 21-

interactive/s/11689784?utm\_source=Focus%20on%20tech&utm\_medium=twit&utm\_campaign=mc%20mag%20SPRING%2021

<sup>&</sup>lt;sup>12</sup> Of course, the measurement of health-sector productivity would have to pick up these digitalisation effects.

<sup>&</sup>lt;sup>13</sup> Roughly 50% of the decline is driven by those ages 16-24. One could assume that this age group returns to the labour force once fully vaccinated.

on furlough in this age group opt to take early retirement? Whilst we do not know the answer to these questions in the particular circumstances of the pandemic, historical evidence is that participation rates are quite elastic. **Figure 3** shows the often sharp moves in over-50s activity rates, on top of the secular rise in their activity over the past 20 years. A permanent fall in activity would be a significant deviation from this past behaviour.



Figure 3: Activity rate for the over 50s

Understanding the level of mismatch<sup>14</sup> in the labour market – one of the drivers of long-run unemployment – has taken on more importance as the economy emerges from Covid restrictions. The basic measure of industry mismatch starts from the idea that mismatch is high when unemployment is high in one sector but job postings are high in another sector (in geographical mismatch, when unemployment is high in one region but job openings are high in another). Thus mismatch is high when the co-variance between the pattern of unemployment and vacancies is low. Mismatch is also high, regardless of co-variance, when unemployment and vacancies are widely dispersed (since the process of matching workers with vacancies is easier with less dispersion).

**Figure 4** shows a number of industry mismatch indicators following <u>Sahin et al</u> (2014). The basic index, reflecting the co-variance and dispersion of the unemployed and vacancies, is shown in the blue line. As you can see, after rising sharply at the onset of the pandemic, this has fallen back in the more recent data to May.

To account for furlough, we can add fully-furloughed workers to unemployment (green line) and fully-furloughed workers who report searching for work to unemployment (pink line).

What do we learn from the fact that the two lines move in opposite directions? The elevated green line is consistent with the idea that furloughed workers are in industries with few vacancies, which makes sense, if

Source: ONS

ii. Mismatch

<sup>&</sup>lt;sup>14</sup> Persistent mismatch can be a sign of large structural change in the economy.

those industries have been closed down. The falling blue line is consistent with the idea that if there are vacancies, furloughed workers are searching. If vacancies emerge as the economy unlocks (the last data point is May 2021) then furloughed workers should start searching.

# Figure 4: Mismatch



Note: Data to May 2021. Estimates of sectoral mismatch are based on Sahin et al (2014). The blue line is the standard approach using official unemployment and vacancies. The green line adds those on furlough by sector to the unemployment series. The pink line adds those on furlough by sector who are searching for work to the unemployment series. Furlough figures to May are based on those on full furlough.

It is an encouraging sign that these measures show the level of mismatch appears to be declining sharply. **Figure 5** looks at another dimension of vacancies, namely their duration. Vacancy duration has declined markedly since 2019. The fact that vacancies in 2021 are currently being filled very quickly suggests a healthy matching process.

# Figure 5: Days job advert remains online



Source: Indeed. Note: Duration measures the number of days a job posting is visible on the www.Indeed.co.uk website. Averages are; 2019 = 25 days; 2020 = 22 days; 2021 (to May) = 18 days.

Another indication of whether the furloughed will return to employment at the end of the scheme i.e. if their skills still match the job requirements, is to look at those on partial and full furlough. A sign that at least some furloughed workers might not be re-absorbed is if the unwind in furlough following the easing restrictions results in only those on partial furlough, who are more attached to their place of work and utilising their skills, regaining their jobs. Not taking fully furloughed staff back might imply that their skills are no longer useful. As **Figure 6** shows, encouragingly, much of the decline in furlough seems to have been in full-time furlough, with workers presumably returning to employment. One caveat here though is that we don't know if these people are going back to work or to inactivity.



### Figure 6: Furlough share

Source: HMRC CJRS

Note: Monthly figures refer to the end of month. Percentages indicate the share of total furlough for that type. These will not sum to 100 due to unclassified types of furlough in the dataset.

Finally, what of the most recent weeks? The timeliness of our mismatch estimates is limited by the LFS, where data for unemployment is currently available up to May. However in recent months the variation in vacancy dispersion has been driving the mismatch index. ONS vacancy data is already available for early June, and <u>published</u> Adzuna data covers up to early July. **Figure 7** shows that the variation in ONS vacancy data closely matches the movements in the variation of Adzuna online vacancy data. As the figure shows, using data up to 9<sup>th</sup> July, there may have been some downward pressure on mismatch.<sup>15</sup>

<sup>&</sup>lt;sup>15</sup> It's worth highlighting that the sectoral vacancy data are assembled at a relatively high level of aggregation, such that within-sector movements are masked.

# Figure 7: ONS and Adzuna vacancy data



Source: ONS. Note: ONS June job vacancy snapshot was taken on 4th June. Weekly Adzuna online vacancy data to 9th July.

# 6. Supply and policy

So far I've discussed some reasons for optimism on the supply side of the economy. But what does this mean for monetary policy?

You might imagine that more supply means *looser* monetary policy. After all, more efficiency in the economy surely means lower prices and hence less inflation. This creates more room to "run the economy hot". But there are two countervailing effects. More efficiency raises future growth prospects. If consumers are at all forward-looking, they might start spending and investing now in anticipation. That boosts demand, in advance of the rise in supply, and so inflation. Thus more supply means *tighter* monetary policy. A second effect is that more growth might raise the underlying "neutral" rate of interest, so-called "R star", necessitating a rise in the policy rate, other things equal. How then are we to think this through?

Regarding the longer-run expected interest rate R star, economic theory models R\* as a function of time preference (patience), population growth, productivity growth and risk. Expected productivity growth raises expected future incomes and expected future living standards. The fact that tomorrow looks better than today depresses demand for saving in safe assets, which causes their price to fall (yields to rise) as households and businesses look to invest in productive assets for tomorrow and consume more today with greater confidence about tomorrow. This is consistent with some of the moves seen in real government bond yields since the start of year. They have moved closer to their pre-pandemic levels and signalled greater certainty of a return to pre-pandemic economic conditions. Now, the R\* is related to output growth and if levels are higher than expected growth might be somewhat higher. But recall that a return to pre-pandemic conditions does not mean roaring growth but rather a return to the relatively low levels of productivity growth that prevailed after the financial crisis of around ½% a year, and the accompanying relatively low interest rates.

Turning to "running the economy hotter", monetary policymakers make judgements concerning the output gap today defined as

$$Output \ Gap = \frac{y - y^*}{y^*}$$
[11]

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Where y\* is the level of feasible supply. An output gap is an imbalance between demand and supply that, all else equal, leads to a deviation of inflation from its target.

Supply (y\*) is generally thought to be slow-moving because it takes time for the economy to efficiently reallocate capital and labour and scale up new ideas. But y\* is not always slow-moving. The pandemic is a timely illustration of this. Prior to 2020 the MPC judged y\* to be growing at around 1-1½% per year. But in 2020 actual output fell by 20% percent. Did supply carry on growing at 1-1½%? No, the MPC judged that supply fell closely in line with demand, as the same economic restrictions that caused demand to fall by 20% also constrained supply by forcing businesses to close and furlough workers. Therefore, despite the seemingly vast amounts of physical spare capacity in 2020, in the sense that no capital was destroyed, in an inflationary sense there was much less spare. As the economy reopens and we see demand rebound, we will also see supply rebound quickly as furloughed workers return to their jobs and companies scale up to higher levels of operation.

Looking past these sharper recent movements in supply, how should one think about less scarring in the context of the output gap? Less scarring means higher y\*, as the productive capacity of the economy is closer to its pre-pandemic trend. For *a given y*, equation 11 would suggest a more negative output gap in the medium term due to higher supply and hence lower inflation.

So what determines y? How can the possibility of future changes in supply change demand now? When households are sufficiently forward-looking, anticipated higher supply in the future should raise wage expectations, brighten employment prospects and encourage investment and consumption now. Indeed, y might even get ahead of y\* if, for example, consumers start spending now in anticipation of a better future path of income Thus if there is more supply there is no presumption that monetary policy should be looser. Rather, the implications for monetary policy can be thought of as a race between the additional capacity, implying loose policy, but additional demand, implying tighter policy.

**Figure 8** gives a sense of that race by considering the paths for monetary policy under two modelled scenarios. It plots the response of a model economy to a 1 percent increase in underlying productivity, TFP. The dashed line shows the response when the change in TFP occurs at the start of the period, but is *unanticipated* and the solid line shows the response when it occurs in four quarters time, but is *anticipated*. Ultimately, in both scenarios the level of TFP is 1 percent higher, but as the top row shows, output and productivity rise by a bit more than 1 percentage point, thanks to a higher capital stock.

The lower panels show how inflation and the policy rate vary, with the interest rate modelled as a Taylor rule (that is, the Central Bank responds to deviations of inflation from target). So the policy rate should be thought of as an illustrative prediction of how a fictional Central Bank might respond to this change. As the lower row shows, inflation and the monetary policy rate eventually return to their starting position.

What is different however is the initial response of inflation and the policy rate. When households anticipate the TFP increase or 'better times ahead', they start to consume and invest more today in anticipation, despite the fact that supply is not quite ready for them to do so. This creates a positive output gap which would cause a

rule-based policy maker to tighten policy to keep inflation in check: as shown by the two peaking solid lines. In the unanticipated case however, prices fall, as the time it takes for demand, prices, wages and investment to adjust to the new level of productivity creates a temporarily negative output gap. In this instance, the monetary policy maker would respond by temporarily loosening policy: the dotted lines.



# Figure 8: Anticipated v unanticipated shocks

Note: Figure plots the simulated responses for selected variables under two scenarios in a medium scale DSGE model based on the Bank of England's own forecasting model Compass (2013). The unanticipated scenario shows the response to an unanticipated one time one percent increase in TFP. The anticipated scenarios shows the response when the increase in TFP is correctly anticipated by households and businesses four quarters ahead. Inflation is the difference in percentage points from the target. The policy rate is the change in the level of the short-term interest rate set by the Central Bank under a Taylor rule. Output and productivity are percentage differences from a counterfactual of no change in TFP.

How does this relate to where we are today? I would argue that the forward-looking scenario is relevant. The vaccines have created a future roadmap out of the economic restrictions created by the pandemic. The data would seem to accord with this view as well. Forward-looking measures like vacancies are now above their pre-pandemic level, forward-looking PMIs are generally net positive, input prices have risen significantly and CPI inflation moved above target in May for the first time since July 2019.<sup>16</sup> So should real policy-makers follow the mechanical Taylor Rule and raise rates?

I would argue not for a number of reasons.

<sup>&</sup>lt;sup>16</sup> The savings rate might be regarded as another reflection of forward-looking behaviour, but of course, it depends upon other factors, such as attitude to risk, which are likely elevated at the moment.

The first is base effects. Starting in March 2020 when oil prices fell by over 60%, energy prices weighed on CPI inflation over 2020 by around 1 percentage point on average. Had energy prices stayed at that low level until today, we'd have expected a purely mechanical rise in the CPI inflation readings from April, reflecting base effects. These refer to the effects of large changes in prices dropping out of the annual comparison of the CPI index. Since March 2020 oil prices have actually rebounded and now sit 40 percent above their pre-pandemic level. This will provide an even greater temporary boost to expected CPI inflation readings to above 3 percent by the end of the year. Almost half of that increase from today is accounted for by energy prices. Base effects are also present in other key indicators like output and wages. The drop in pay in the spring and summer of 2020 will continue to distort annual comparisons.

Secondly, like in the simulation above, these pressures and erratic data readings should be temporary and therefore could be looked through. This was our policy in October 2011 when CPI inflation rose as high as 5 percent on the back of oil prices rising to over 120 dollars a barrel. It was also the case after the Brexit referendum when CPI inflation rose to 3 percent in 2017 after sterling's depreciation of around 20 percent in 2016. What's important is that people understand these are temporary pressures and, like in the simulation above, they understand that if these temporary pressures were to become more permanent the central bank would react accordingly. So far the stability of inflation expectation readings indicates the temporary nature of these pressures is well understood but I will watch closely for any signs that this might change.

Thirdly, it is important to remember that even if the future looks brighter, we are at the moment fighting to get back to where we were and we are not there yet. The Delta variant currently spreading exponentially in the UK has an R number of 1.5.<sup>17</sup> It is now showing signs of rapid progress in our European neighbours. A recent study by my colleagues at Imperial College,<sup>18</sup> published on GOV.UK, shows the impact of changes in R on hospitalisation rates. The simulations show that in the central scenario where the Delta variant is 65% more infectious than the UK (now Alpha) variant, hospital bed occupancy would peak at around 32,000. But if Delta turned out to be 80% more infectious than Alpha, the peak occupancy would jump to nearly 90,000 beds - that's over double the 40,000 beds occupied at the peak of the second wave in January. The sensitivity of the public health situation to changes in Delta's relative infectiousness, as documented in this study, is a reminder that new variants can knock us off course. The possibility of further mutant strains, pressures on the NHS and many "pinged" workers make our path to recovery fragile.

Finally, the majority of the recovery to date has occurred under the protective blanket of the government employment schemes, loan schemes, tax relief and insolvency/eviction protections. Many of these have only just recently expired and more will expire by the autumn, notably the furlough scheme, the self-employed support scheme and the £20 Universal Credit uplift which are scheduled to end in September. On Universal Credit, notice that the implied reductions are about 25% for a single adult and 17% for couples.<sup>19</sup> Tax relief

<sup>&</sup>lt;sup>17</sup> See Delta variant could cause significant third wave - latest Imperial modelling | Imperial News | Imperial College London

 <sup>&</sup>lt;sup>18</sup> See <u>S1289 Imperial Roadmap Step 4.pdf (publishing.service.gov.uk)</u>
 <sup>19</sup> The £20 per week boost has set the monthly basic rate in 2020-21 at £410 for a single adult, and £594 for a couple, rather than £323 and £507 respectively (adults aged 24 or younger receive reduced rates; additions for children, health conditions and caring are unchanged).

policies such as the hospitality VAT reduction and the business-rate holiday are also being gradually phased out by year-end or early next year.

# 7. Conclusion

The immense support for the economy over the pandemic looks like it might have averted deep scarring. The anticipation of an improved future might well feed into demand today and so add to inflationary pressure. But much of inflation will be high temporarily due to the low base from which prices are rising. In addition the economy is fully not recovered yet and faces two headwinds over the coming months: the highly transmissible Delta variant and a tightening of the fiscal stance. Against this backdrop, risk-management considerations lean against a pre-emptive tightening of monetary policy until we can be more sure the economy is recovering in a manner consistent with the sustained achievement of the inflation target. For now, tight policy is not the right policy.

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# Appendix

Table A1 provides more detail concerning the calculations in Table 3.

# Table A1

	Change in capital stock by 2024 (pp)							
	(1)	(2)	(3)	(4)	(5)	(6)		
Buildings	0.1	-1.0	-0.2	1.3	-2.3	-2.3		
Intangible	1.6	-2.5	-1.4	7.5	-3.4	10.7		
Tangible	-5.5	-3.2	-4.0	-8.3	-2.0	-6.9		
Total	-2.6	-2.3	-2.4	-2.7	-2.3	-2.9		
	Capital scarring contribution (pp on GDP)							
Buildings	0.0	0.0	0.0	0.0	0.0	0.0		
Intangible	0.1	-0.1	-0.1	0.4	-0.2	0.6		
Tangible	-0.9	-0.5	-0.7	-1.4	-0.3	-1.1		
Spillovers	0.3	-0.5	-0.3	1.5	-0.7	2.1		
Total	-0.5	-1.2	-1.0	0.5	-1.2	1.6		
Memo								
Total Scar. w/buildings	-0.5	-1.3	-1.0	0.7	-1.5	1.3		

Note: Table sets out the contribution of capital scarring channels to the change in potential output by 2024Q2. The exercise conditions on the business investment forecast embedded in the January 2020 and May 2021 Bank of England forecasts. The capital channels multiply the change in capital stocks by each assets share of capital income  $s_i$  and overall capital share  $\alpha$ , assumed to be a third. Capital stocks are built up using a perpetual inventory method with annualised deprecation factors of (0.05, 0.10, 0.30) respectively for buildings, tangible and intangible assets. A spillovers coefficient is  $\gamma = [0.1, 0.2]$ , (0.2 shown above) is applied to the change in the intangible capital stock based on Corrado et al (2017). Total scarring from non-human capital is therefore:  $dy = \alpha(s_b dk_b + s_I dk_I + s_T dk_T) + \gamma dk_I$ .

In the baseline calculation buildings are assumed to not effect the level of capital services. Each column (1) - (6) represents a different assumption about the share of investment accruing to different assets over the period 2021Q1-2024Q2 in the May 2021 forecast. (1) assumes a slow linear in time unwind of investment shares from their observed shares in 2020 to their 'historic' 2015-2019 average share by 2024Q2. In (2) investment shares immediately revert to their historic average in 2021Q1. In (3) they revert as a function of the difference in the level of investment between the two forecasts. In (4) shares stay at the 2020 level throughout the forecast. In (5) real buildings investment remains flat at the 2020 level and residual business investment is allocated to tangible and intangible investment in line with the historic relative shares. (6) repeats (5) but allocates to tangible and intangible investment in line with the 2020 relative shares.

# **Furlough share**

As stated in the footnote to Table 1, the furlough share (column 4) is the full-time equivalent furlough divided by the labour force. Those on furlough consist of those on the CJRS (employees) and SEISS (self-employed). In

calculating full-time equivalent furlough, I assume full-time furloughed work zero hours while those on flexifurlough and the SEISS work 50% of their usual hours.

These simplifying assumptions mean that the furlough share may be overstated – and consequently, boost the average hours excluding furloughed workers in table 1 (column 6).

While we count a fully furloughed worker as working zero hours, they are allowed to take up another job and so could appear in the LFS data in column 2d, boosting average hours worked.

The assumption that flexi-furloughed staff work 50% of their hours is derived from the LFS micro data (LFS data as at 9<sup>th</sup> July 2021) although this, in reality, can vary quarter to quarter. The assumption that those who applied to the SEISS work 50% of their regular hours is simply matching the flexi-furlough assumption above.

The labour force used as the denominator in column 4 of the table may overstate the true portion of workers on furlough. The furlough data is published by HMRC and is on a per worker basis, i.e. a person can work several jobs and thus could appear in the furlough data more than once. The labour force data surveys people to see if they are in employment or not (but are searching for work). A person is counted as being in employment as long as they worked at least one hour in the previous week or who had a job and were absent. It does not distinguish if the person had more than 2 jobs.

Finally the majority of those furloughed have come from sectors with lower average hours per worker than the typical worker. But, for the purposes of Table 1, we treat these people as working the typical average hours worked. This may overstate the FTE furlough share and thus the average hours excluding furlough (columns 5 and 6 in Table 1).