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"Potential Capital," Working From Home, and Economic Resilience

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Abstract

The impact of an economic shock depends both on its severity and the resilience of the economic response. Resilience can include the ability to relocate factors, for example, even when new technologies or skills are not yet at the ready. This resilience per se buffers production and has an economic value, which the researchers estimate. The COVID-19 pandemic caused a widespread decline in recorded gross domestic product (GDP). Yet, as catastrophic as the collapse was, it was buffered by an unprecedented and spontaneous deployment of what the authors call "Potential Capital," the dwelling/residential capital and connective technologies used alongside working from home. Together potential capital and labor working from home provided additional output margins and capacity. The researchers estimate the contribution of this capital, and the remote work that it facilitated, to have roughly halved the decline in GDP in the U.S., reducing the fall in GDP to 9.4 log points in the second quarter of 2020 at the trough of the recession. Similar effects are seen in the six OECD countries for which data are available; output fell by 14 log points, but would have fallen by 26 log points had only workplace inputs been available. Accounting for the contribution of "Potential Capital" also revises downwards estimated total productivity gains in the business sector during the pandemic from 8 log points to 5 log points in the second quarter of 2020. The authors also find an output elasticity of domestic non-dwellings capital to be similar to that of workplace ICT capital, reflecting its role as productive capital. Turning to the future, changes in working from home depend upon relative costs, relative technologies and, crucially, the elasticity of substitution between home and work tasks. Eberly, Haskel, and Mizen estimate that elasticity to be more than unity, meaning that the growth of ICT will raise the share of work done remotely.

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1 Introduction

Large shocks test an economy's ability to adapt, adjust, and continue production – a capability called "resilience" – in response to the unexpected. Technologies, factors, and skills may be fixed, at least in the short run. Critical infrastructure may be damaged or unavailable, leaving other systems stretched beyond capacity. Whether a natural disaster, terrorism or cyber attacks, or a global pandemic, the severity of a crisis is determined not only by the size of the shock, but also by the resilience of the response. Accordingly, risk professionals, regulators, and others emphasize the development of resilience (or "business resilience" in the private sector) as a buffer against such shocks. This often includes redundant critical systems, cross-training employees, and interestingly, back up work locations.

The COVID-19 economic and health crisis greatly stressed all these preparations, but in some cases also elicited unplanned resilience. We argue that fungibility of factors of production at different locations contributed substantially to economic resilience during the COVID-19 pandemic. This required not only the much-discussed ability of some (fortunate) workers to work from home, but also the capital they needed to deploy from these remote-from-work locations, including the capital that connects them to each other and the workplace. We call this "Potential Capital".[1] Conceptually, it is the equipment – home offices, laptop computers and internet connections – that can be combined with remote-from-workplace labor to produce output.

Consider the Covid pandemic – one of the largest economic shocks in living memory – the largest in three hundred years for some countries.[1] The dark bars in figure 1, show the peak to trough (2020Q1 to Q2) actual decline in GDP for the seven countries we study in this paper. The decline is dramatic: it shows quarterly declines of between 9 and 20 log points.[2] Yet, catastrophic as the collapse was, it could have been worse. Many workplaces were closed and people were advised to isolate and to work from home (WFH). As we shall document, since much of the workforce was working from home, there was a fall in hours *at the workplace* of nearly 30 log points from 2020Q1 to 2020Q2 (an unweighted average in our seven countries). Based on an output elasticity of two-thirds, output should have fallen by 20 log points, far more than the actual (average) drop of 14 log points. Thus the first

[1] Given this capital was pre-existing but unused, we call the capital at home "potential capital" because it was domestically-located capital and was capable of being deployed in business activities but had not previously been used for work purposes.

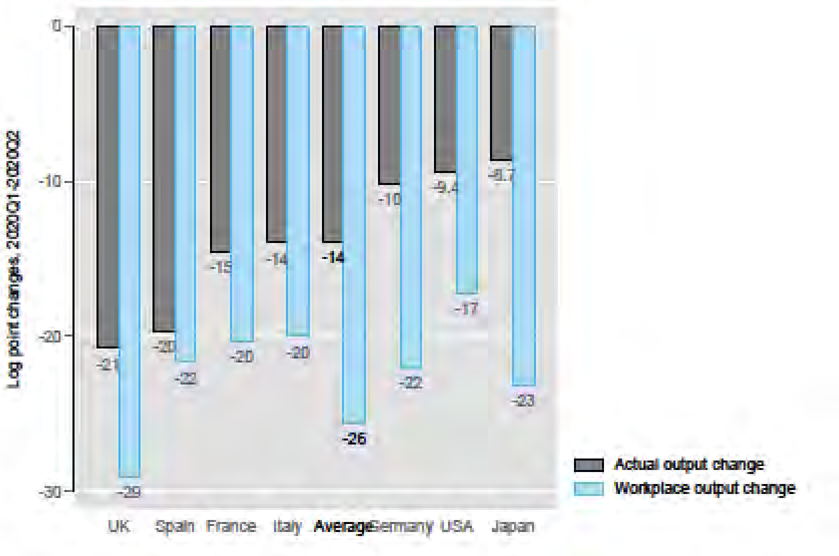
[1] Wall Street Journal Feb 12, 2021, U.K. Economy Suffers Biggest Slump in 300 Years Amid Covid-19 Lockdowns.

[2] We use natural log changes (times 100) throughout to be consistent with implementation of our growth accounting framework in section 2. For a change to y from x, the log point change = 100*ln(y/x).

puzzle: why did output fall by so *little* in response to these large changes in hours at the workplace? Or was it buffered by economic resilience arising from remote labor?

A second puzzle emerges if we consider capital in addition to labor. As (Mokyr 2001) documents, the history of industrialisation shows the point of going to the workplace is that workers have capital with which to work.[3] It seems hard to believe that the economy substituted a 30 log point fall of hours with a rise in workplace capital in a matter of weeks. Rather, with fewer workers at the workplace, it seems very likely that workplace capital utilization also fell. Based on industrial electricity consumption, we estimate a fall in capital use at the workplace of just over 20 log points, which with an output elasticity of one-third, should have reduced output by a *further* 7 log points. Thus in Figure 1, the light bars, which are the implied workplace output changes, lie below actual bars illustrating our puzzle: why did output fall by so *little* in response to these large changes at the workplace? Expanding our question above, was the decline in output further buffered by capital deployed from home?

Figure 1: Actual and workplace implied output loss, 2020Q1-Q2



Notes: Actual Output is the decline in GDP from Q1 to Q2 of 2020 in National Accounts data. Workplace Output is calculated based on factor use at the workplace, from Eurostat, BEA, National Accounts and own calculations, see data appendix. Work from home from ONS and Google mobility data is described in the appendix. Average is an unweighted average of all countries.

[3] As (Mokyr 2001) also notes, the pre-factory era was one where capital (typically rudimentary textile equipment) was located at home. It was the rise of the factory method of production that co-located capital and labor in the workplace.

The novelty we introduce in this paper in answer to these puzzles is that capital equipment and structures at home were brought into use for production providing the capacity to respond to a large unanticipated shock. During Covid, potential capital alongside labor working from home helped to offset the expected decline in output due to low workplace labor and capital utilization rates, which explains why output did not fall as much as it might have done. Production was buffered by use of capital and labor at home.

Once we recognise potential capital, it opens up new perspectives on several issues. First, it introduces a distinction that we will refer to repeatedly – that there is labor and capital in the workplace and labor and capital at home, and both can contribute to production. Not every industry is able to utilize labor at home and potential capital to the same extent, but the industries that can use them make enough of a contribution to output to make a difference at the national level (Bloom et al. 2020)(Bloom, Fletcher, and Yeh 2021). Thus in this paper we seek to document the use of such capital at home alongside labor at home.[4]

Second, productive labor and capital at home gives firms flexibility to respond to a large shock like Covid. Fungibility between capital and labour at home and the workplace is often a source of economic resilience. This is made possible because the capital at home has both productive capacity (e.g. can run software) and connectivity with other workers making home working both possible and productive. It probably wasn't possible, or quite so productive, with technologies of earlier decades, but technology has advanced so that it is of lower cost now. This raises the question of whether part of the value of the internet is in bringing resilience to economic output: we seek to estimate this value.

Third, in the future, how much use will firms make of potential capital? Will there be more working from home? Popular discussion takes it as near-axiomatic that now that economies have shown they have the capability to work from home, more labor will be at home. But price theory tells us that a rise in productivity of working from home means *fewer* workers at home if the elasticity of substitution between work and home tasks is low (<1). This ambiguity is reflected in historical experience. Domestic workers became vastly more productive with the advent of domestic appliances, but the numbers of these workers working at home collapsed.[5]

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[4] This point is reminiscent of the GDP boundary issue, Coyle, 2014, namely that durable goods at home are a potential source of capital services for market-sector output. Recent work on the "gig" economy has further tested the GDP boundary: the part-time driver for example who uses their domestic vehicle for commercial rides. This reflects unused capacity in passenger vehicles, used only 5% of the time (Shoup 2011), or in unused accommodation, rooms, houses, and holiday homes available for rent. Nor are these issues just confined to the national boundaries since offshoring is yet another instance of the geographical separation of capital and labor (although not a shift to production at home). Yet, none of these explorations envisioned the deployment of home capital at the scale and speed, with the potential consequences, observed in the context of the Covid-19 crisis.

[5] By contrast, washing machines relocated laundry to a task performed at home: the commercial laundry business (who would do domestic laundry in commercial premises) completely disappeared (as Mokyr reports that despite mechanisation, time spent on home laundry in the United States increased from about 5.5 to over six hours per week between 1925 and 1964). As we discuss below, there are two issues here: the location of market work at home/premises and the division between market and non-market work. Thus a fall in the use of domestic servants is a decline in market work at home margin, whereas the (puzzle of the) rise in hours spent on domestic tasks,

There has already been a proliferation of literature based on survey evidence documenting the shift towards working from home ((Barrero, Bloom, and Davis 2020a);(Barrero, Bloom, Davis and Meyer 2021; Haskel (2020); Mizen. Bloom and Taneja, 2020; Taneja, Mizen and Bloom, 2020; Taylor and Griffith 2020) and earlier by Bloom et al (2015), with evidence of occupations and industries with a high share of tasks that can be done from home ((Bartik et al. 2020; Dingel and Neiman 2020). There is little doubt that some businesses can work from home, but there has been much less discussion of capital at home - which facilitates the ability of labor to work off-premises and buffer the impact of Covid. Nor has there been, to the best of our knowledge, an estimate of the extent and value of that capital and the elasticity of substitution between home and work.

Our main findings are first to document the extent to which labor and capital at home buffered the decline in workplace output, making aggregate output more resilient to the COVID shock and resulting collapse in GDP, a quality emphasized by Brunnermeier (2021). We estimate that across our sample of countries, the resilience of domestic production that "saved" 12 log points of GDP 2020Q1-Q2 (Figure 1) consisted of a contribution from labour working remotely of 8 log points, and potential capital 3 log points. Second, we estimate that the elasticity of output with respect to the non-dwellings component of home capital is between 4 and 14 percent, comparable to the 5% elasticity of output with respect to business sector ICT[6]. Third, we are able to estimate the elasticity of substitution between labor at work and at home, which is consistently greater than one. This implies what many have assumed, which is the greater productivity of labor at home is likely to increase working from home, rather than the opposite. Finally, we emphasize that the shift to work from home is largest in industries which had higher existing stocks of ICT capital, suggesting the important role of investment and technology in facilitating resilience.

The rest of the paper proceeds as follows. In the next section, we extend a growth accounting framework to allow for production at work and at home and use this structure to estimate the contribution of each sector and that of TFP across a panel of seven developed economies. Section 3 estimates the elasticity of substitution between labor at work and at home and focuses on the longer run outlook for working from home. Section 4 draws together the findings and offers implications and conclusions.

2 Structure for Growth Accounting

Our first objective is to assess the use and value of capital at home. We use a standard growth accounting framework, augmented by home and work factors, to structure the analysis. We use this to address a

despite mechanisation, is at least in part a market/non-market work margin decision (for more on this puzzle see below and .(Cowan 1983; Mokyr 2000; Ramey 2009).

[6] That is, the share of business sector ICT rental payments in value added is about 5% in advanced economies.

counter-factual: what would have happened to output had everyone who was at home had no capital with which to work?[7]

2.1 Framework

Suppose the economy's production possibility frontier defines output that can be produced by labor and capital services, and capital and labor in turn can be located at home (H) or at work (W)

$$Y = F(K*_W, K*_H, L*_W, L*_H), \tag{1}$$

where the stars denote flows of services including knowledge services. We will assume the standard structure for growth accounting and TFP estimation, that is, constant returns to scale, perfect competition, and optimizing behavior.[8] So as to isolate the effects of interest, the only deviation is to add home versus workplace production. Changes in output, Y, are therefore changes in the inputs times their output elasticities. We suppose that labor services, L*, are hours and capital services, K*, are capital (later we shall write capital services as product of capital stocks and capital utilisation: we suppress this for now to ease notation).[9] Let superscripts W and H denotes workplace and home respectively and P_Y is the output deflator, we write

$$\frac{P_Y Y^W}{\sum P_Y Y} dy^W + \frac{P_Y Y^H}{\sum P_Y Y} dy^H = \varepsilon_Y^L \left(\varepsilon_L^{L^W} dl^W + \varepsilon_L^{L^H} dl^H \right) + \varepsilon_Y^K \left(\varepsilon_K^{K^W} dk^W + \varepsilon_K^{K^H} dk^H \right) \tag{2}$$
$$+ \frac{P_Y Y^W}{\sum P_Y Y} dtfp^W + \frac{P_Y Y^H}{\sum P_Y Y} dtfp^H,$$

where ε is an elasticity with respect to each factor, and lower case letters are logs, so dz equals change in lnZ. The growth in total nominal output (Y^W and Y^H being output produced at the workplace and home respectively) is the growth in labor hours at work and at home (H^W and H^H), times the relevant elasticities, and similarly for capital services at work and at home (K^W and K^H), plus the contributions of total factor productivity at work and at home. If markets are competitive, and if labor and capital are

[7] We will also consider a counterfactual with no work from home, as the extreme case.

[8] While these assumptions are standard, they are not necessarily innocuous. (Crouzet and Eberly 2018) demonstrate the impact for TFP measurement of relaxing perfect competition and allowing for errors in capital measurement, which can be substantial.

[9] There are a host of issues around utilization and whether it should be subsumed into the capital payments term. Here we are trying to capture the idea that, say, an office building under lockdown offers fewer capital services not because the capital has been destroyed, but the utilization of such capital has changed. In Berndt-Fuss-Hulten ((Berndt and Fuss 1986; Hulten 1986)), such a change in capital services would be reflected in the price of such capital (which would presumably fall -- potentially drastically depending on the length of the change); the capital payments share would fall and hence the contribution of capital services in the production function (the share times the capital) would fall. With, for example, sticky rental prices, such a change might not show up in share changes.

paid for the use of their services, optimising owners of capital and labor implies that we can simplify to substitute labor and capital shares for the elasticities

$$dy = s_{P_Y Y}^{P_L L}\left(\frac{P_{L_W}L^W}{\sum P_L L}dl^W + \frac{P_{L_H}L^H}{\sum P_L L}dl^H\right) + s_{P_Y Y}^{P_K K}\left(\frac{P_{K_W}K^W}{\sum P_K K}dk^W + \frac{P_{K_H}K^H}{\sum P_K K}dk^H\right) + dtfp$$

$$\text{where } s_{P_Y Y}^{P_L L} \equiv \frac{\sum P_L L}{\sum P_Y Y} \text{ and } s_{P_Y Y}^{P_K K} \equiv \frac{\sum P_K \boldsymbol{K}}{\sum P_Y Y}. \tag{3}$$

To get at the notion of resilience we rewrite the above in terms of the contribution of labor and capital at work and the additional contribution of labor at home and potential capital, namely

$$\begin{aligned} dy = {} & s_{P_Y Y}^{P_L L}\left(dl^W + \frac{P_{L_H}L^H}{\Sigma P_L L}d(l^H / l^W)\right) \\ & + s_{P_Y Y}^{P_K K}\left(dk^W + \frac{P_{K_H}K^H}{\Sigma P_K K}d(k^H / k^W)\right) \\ & + dtfp \end{aligned} \tag{4}$$

The first and third terms on the right hand side are the conventional production function terms, namely that dy results from dl^W and dk^W times their output elasticities (here the shares). The second and fourth terms are the additional effects, of shifts from W to H, times their output elasticities.

Equation (4) shows that Y falls if L and K *at work* fall, which is conventional, but is offset if L or K migrates to home. The workplace-implied fall in output in Figure 1 is the first and third term and the offsetting effect of working from home and "potential" capital are the second and fourth terms.

To take this structure to the data we adopt two approaches. First, we take a growth accounting approach and attempt to measure the various terms to understand the magnitudes of the contribution from potential capital. Second, we examine the correlates of input use at home relative to work.

2.2 Growth Accounting

To measure the terms in equation (4), we proceed as follows. The left-hand side is (change in log) GDP. On the right-hand side, let us set the L and K shares as 2/3 and 1/3 respectively. Turning to the hours terms, if we assume that labor is paid the same at home or at work, then the payments weights are the share of hours at home and at work.[10]

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[10] We use traditional labor shares for all the countries. We can readily use a smaller labor share for the US, reflecting evidence of declining labor share. This adjustment will raise the importance of potential capital in our calculations, but is small compared to the magnitudes we find overall. The evidence outside the US is less convincing of a change in labor shares. Regarding pay at home and at work, there is not evidence so far that wages and salaries have adjusted during the pandemic to differentiate home versus work on premises. Given our later evidence, this is an interesting topic for future work.

The capital terms are more complicated. Starting with the capital shares, national accounts conventions includes dwellings as (residential) capital, with an associated rental price, suggesting we can measure share of K^H as the dwelling payments as a share of total capital payments. This estimate needs to be adjusted in at least two ways. First, we multiply dwellings capital by labor force participation, assuming that dwellings capital can be potentially brought into production in proportion to the fraction of the population who may potentially be WFH. Second, K^H is not just dwellings capital, but e.g. domestic computers and the internet, which are not counted as investment in national accounts but as consumption. We have no data on this currently. As a result this will appear as an error term in the equation and will contribute to total factor productivity, which we discuss further below.

Turning to the change in capital data it seems reasonable that the major source of change has been in utilisation: official data for the UK at least shows almost no change in measured capital stocks or services: see Appendix.[11] One way to examine this is to look at final commercial and domestic energy use, corrected for seasonality and temperature, and excluding the output of the energy generation sector itself and (the very volatile) transport sector. For domestic capital use, we found that domestic energy use had hardly changed and so proxied log changes in domestic capital use by working from home, reflecting domestic utilisation. Thus if we suppose that the log change in capital services dk*=dk+de where de is the change in log utilization, measured in turn by changes in energy use at work, we write

$$dy = \frac{2}{3}\left(dh^W + \overline{WFH}(dh^H - dh^W)\right) + \frac{1}{3}\left(de^W + \overline{\left(\frac{P_K K^{DWELL}}{\Sigma P_K K}\right)}(de^H - de^W)\right) \qquad (5)$$
$$+dftp$$

where W and H superscripts apply to work and home factors, as previously, and DWELL refers to dwellings, or residential, capital, an overbar is a time average and $WFH=L^H/L$.

Finally, we must account for the possibility of furloughs. In the UK, a furlough policy allowed firms to temporarily suspend workers rather than lay them off, with the government paying 80 percent of their wages (we will say more about this below). Thus these workers were counted as employed, but the work output of these furloughed workers was zero. We have reliable data by sector to measure the proportion of staff in the UK that were furloughed, and we adjust our productivity estimates accordingly.[12] Unfortunately, in continental Europe we do not have the same information about whether

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[11] The lack of change in capital over the period of the pandemic (https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/businessinvestment/apriltojune2021provisionalresults) is to be expected: although there has been minimal investment over the last four or five quarters, 74% of capital is dwellings, buildings and structures which depreciate very slowly. See Appendix for more details.

[12] Workers on furlough were not allowed to work. If they did work, but are not counted as working from home, we will overestimate the value created by those workers who did work from home. However, we find similar results in countries which did not have a furlough program, and where such a bias could not arise.

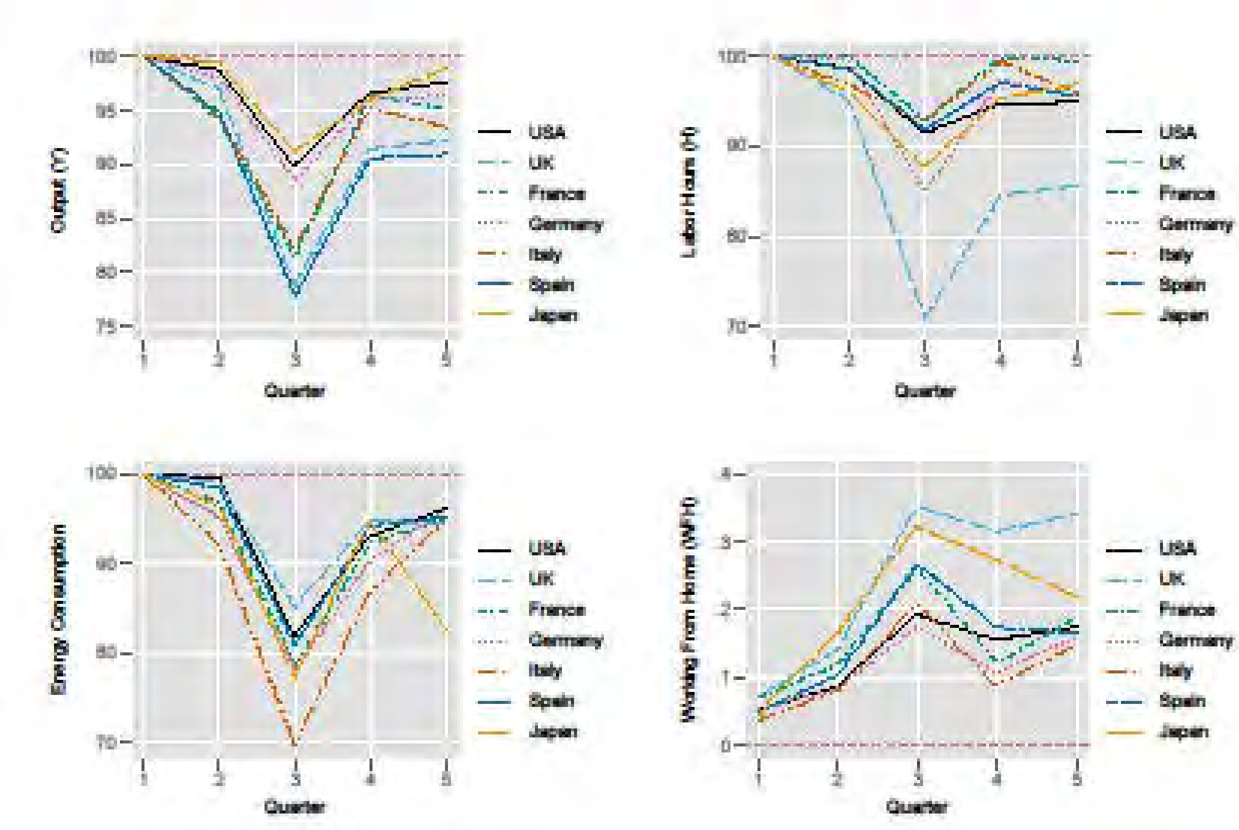
workers were WFH or temporarily suspended. If we were to assume all employees at home were producing output we would distort the estimates of productivity by overstating the proportion WFH, so we adjust the total hours of employees at home to remove those who were *effectively furloughed*. The estimate of the effective furlough by country is based on furlough proportions of employees in the same sector in the UK rescaled using Google mobility data for each country, as described in the data appendix.

2.3 Results

2.3.1 International Evidence

We turn now to the results of the expanded growth accounting exercise from seven advanced economies. Data are drawn from the OECD, Eurostat, ONS and Bank of England, with details provided in the data appendix. Figure 2shows the time series response of four key variables – and index of output, labor hours and energy consumption (100 = 2019Q4) and working-from-home share of the total workforce. The first three indices show the decline in output, labor hours and energy use demonstrating the impact of the shock. The fourth shows the response in the workforce, as the share of working from home increased peaking in 2020Q1 in Japan and 2020Q2 in the remaining six countries.

Figure 2: Output, labour, energy and working from home



Source: authors' calculations from OECD, working from home survey, mobility and energy data. See data appendix.

Figure 3: Changes in home and workplace output

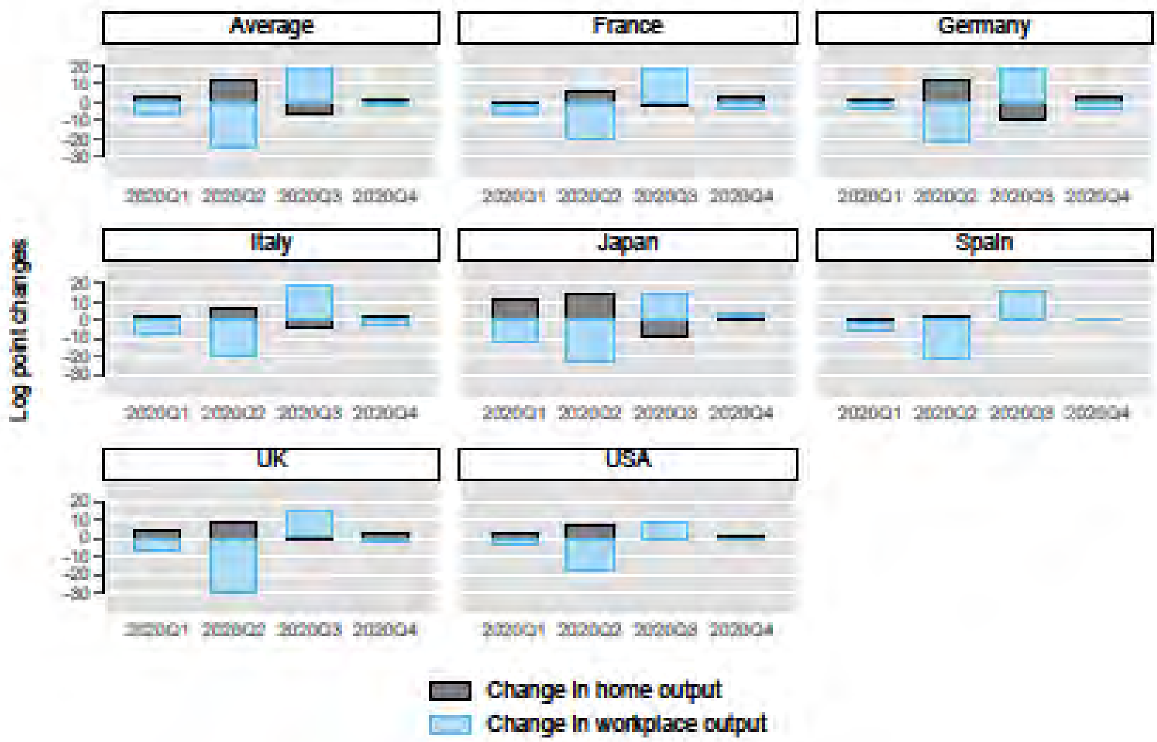


Figure 3 shows log point changes in home and workplace output, as in Figure 1, but for each quarter in 2020. As the lighter bars show, in all countries, workplace output fell in 2020Q1 and precipitously in 2020Q2 but this was offset to a degree by home working, which meant actual output fell by less than output produced at the workplace. After lockdowns were eased in the summer output rebounded across the board. As the darker bars show, home output rose in 2020Q1 and 2020Q2, demonstrating the resilience effect of working from home.

Figure 4: Capital and labour contributions to home and workplace output

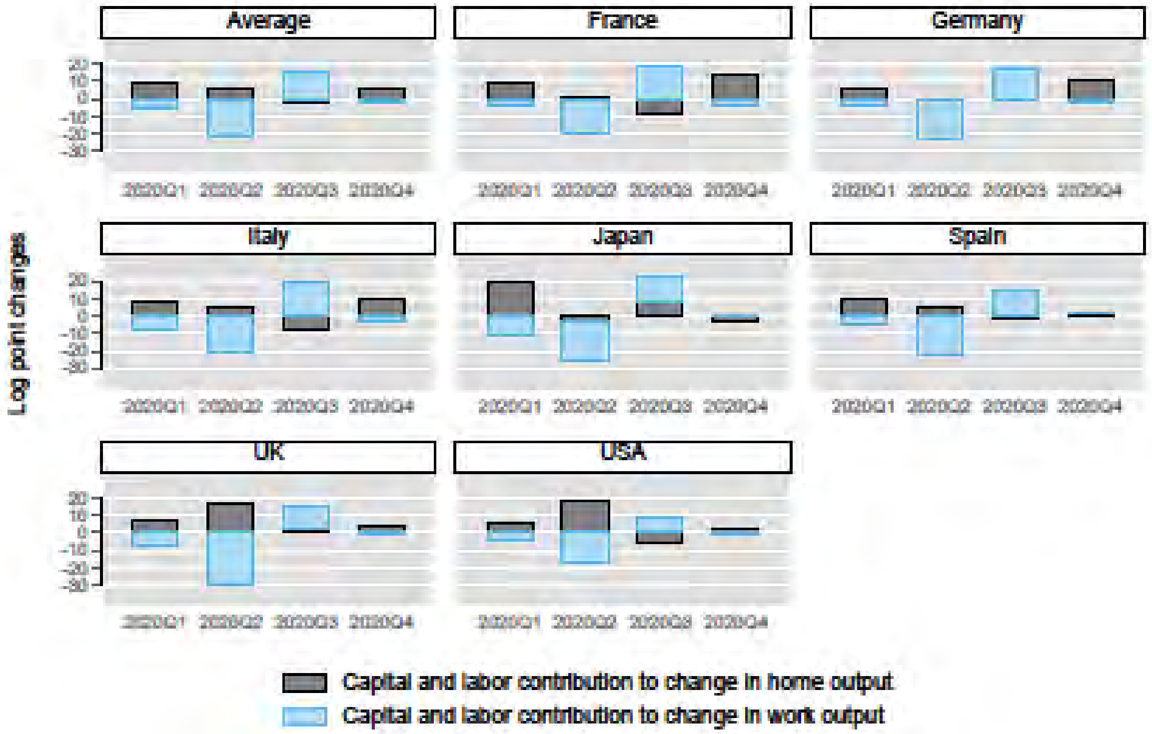


Figure 4 shows the capital and labour contributions to home and workplace output. As the light bars show, the use of inputs at the workplace fell in 2020Q1 and 2020Q2, rising in 2020Q3, and somewhat flatter in 2020Q4. The contributions from home inputs was the opposite: rising in 2020Q1 and Q2 and then falling. Notice that the contributions were considerable in 2020Q1 in all countries, especially in countries where the virus struck relatively early, such as Japan. The data are more mixed in 2020Q2, reflecting the later impact of the virus in the US and UK, where there was a substantial offset from the contribution of home output.

Figure 5: TFP total and implied by workplace inputs

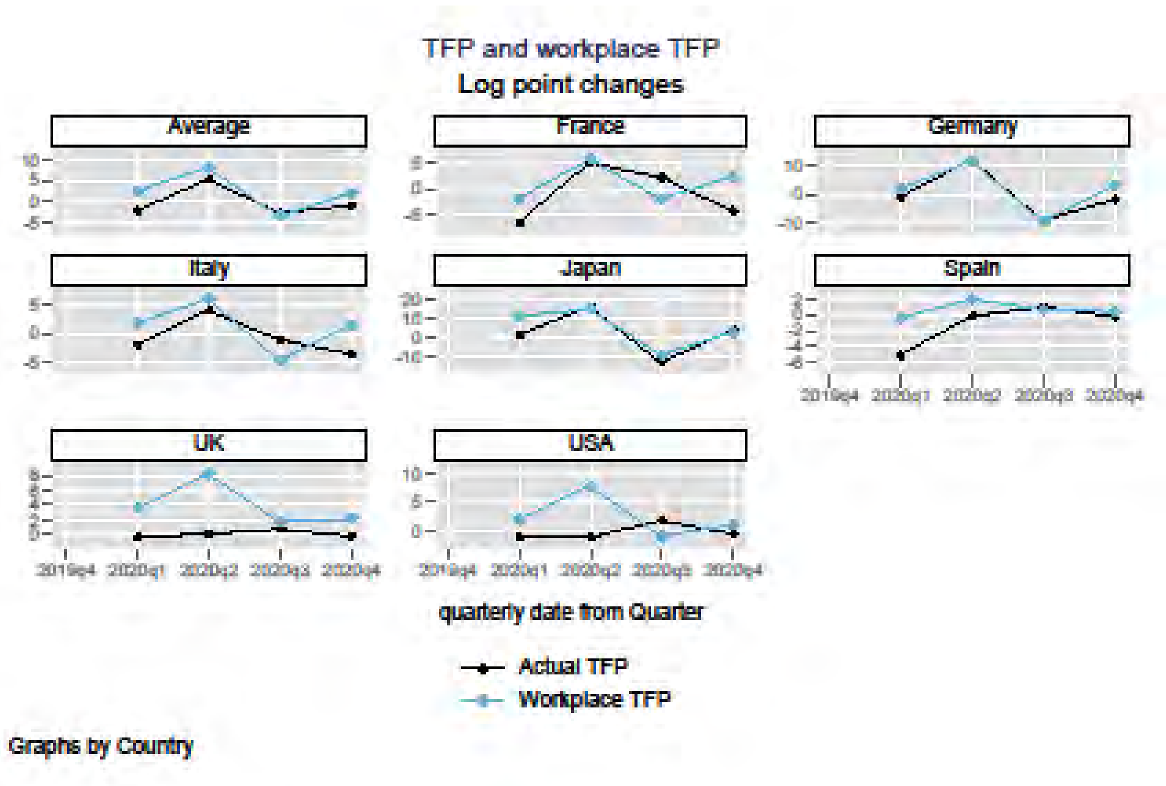


Figure 5 plots the effect on TFP. Workplace TFP takes actual output and subtracts off the contribution of workplace input. This generates an apparent rise in TFP in the UK and USA initially, since these countries had a large cushion from working from home. That is, in those countries the "hidden" input from working from home causes an apparent rise in TFP. There is then a large drop in workplace-based TFP, as resources switch back to the workplace.

In sum, if WFH had been ignored along with potential capital, productivity in the US and the UK would have been exceptionally *strong* in 2020Q1 and 2020Q2, due to mismeasurement of labor and capital inputs to production of goods and services. Ignoring home capital would have been misconstrued as a productivity boom during the pandemic. Similarly, in continental European countries, productivity would have been higher, although not quite the boom that would have been observed in the US and the UK. The exception is Germany, where manufacturing for export continued to produce output without much interruption, but labor hours across all sectors was lower in 2020Q2 than it had been before Covid; after making adjustments for labor and capital at home the boom is still observed.[13]

[13] An index of US and German output follows a similar path in 2020 falling from a 2019Q4 value of 100 to around 98 in 2021Q1 and 89 in 2020Q2 before recovering to 96 in 2020Q3 and 2020Q4. The difference is that in the US the labor hours index took the values 100, 99, 92, 95, 95, while in Germany the index took values 100, 99, 85, 97, 96 hence a much larger increase in 2020Q2.

2.3.2 The value of capital at home

So far we have used the value of dwellings to proxy the value of capital at home. But, as described, consumers have more capital at home than dwellings: the internet, home computers etc. On the assumption that consumers and not firms pay for this capital, it is a spillover to firms. We may ask: what is the implied value of that spillover? As a spillover it is part of measured TFP growth and so we attempt to value it as follows. The changes in capital at home that we measure (since we proxy by changes in home utilisation) are changes in both dwellings (dk^{HD}) and non-dwellings (dk^{HxD}) capital, but weighted equally by the value of dwellings capital, so that measured capital services are

$$dk^{M} = s_K^W dk^W + s_K^H (dk^{HD} + dk^{HxD})$$
$$where \tag{6}$$
$$s_K^W = \left(\frac{P_K K^W}{P_K K^W + P_K K^H} \right), s_K^H = \left(\frac{P_K K^H}{P_K K^W + P_K K^H} \right)$$

Suppose however the true flow of capital services from non-dwellings home capital has a different elasticity, which we write as an addition/subtraction, γ, from the dwellings elasticity

$$dk^{T} = s_K^W dk^W + s_K^H (dk^{HD} + (1+\gamma) dk^{HxD}) \tag{7}$$

Measured TFP growth reflects this excess elasticity (along with other sources of mismeasurement) in the term scaled by γ

$$dtfp^{M} = dtfp + \gamma (s_K^H dk^{HxD}) \tag{8}$$

If we can proxy for underlying TFP and can estimate γ, then we can compute the capital elasticity and output elasticity of non-dwellings home capital, respectively (1+γ) and (1+γ)*(1/3), with the latter assuming that the total capital elasticity is one-third. To help control for underlying TFP we note that there was considerable measured productivity growth due to composition or “batting average” effects over this period, as low productivity sectors (such as food) shrank disproportionately. We therefore add the labour productivity impact of such changes in composition (calculated from industry labour productivity data for all our countries, bar Japan, due to data limitations, see data appendix) to give the regression model

$$dtfp_{i,t}^{M} = \gamma (s_K^H dk^H)_{i,t} + \sigma COMPOS_{i,t} + v_t + v_i + e_{i,t} \tag{9}$$

If dtfp and other country effects are captured by country/time dummies we can obtain an estimate of γ. The first regressor is $s_K{}^H dk^H$ (in practice with no change in dwellings capital over this short time period, dk^{HxD} is driven by increased use of non-dwellings home capital).[14] Thus the identifying variation in this exercise is the large change to working from home: our results would be upward-biased to the extent that households endogenously built up more domestic capital in anticipation of such a change.

The results of this exercise are set out in Table 1, where columns 1 and 2 exclude and include quarter fixed effects, respectively. The coefficient on $s_H{}^K dk^H$ depends on the inclusion of the quarter dummies: it is larger with more controls. Including time effects also renders the composition effect negative.

Table 1: Regression estimates of *(9)*

(dependent variable: $dtfp_{i,t}$)

	(1)	(2)
$s_H{}^K dk^H$	-0.56	-0.89
	(-1.69)	(-3.47)
COMPOS	1.85	-3.98
	(1.19)	(-2.96)
Observations	24	24
Number of ctry	6	6
Quarter FE	No	Yes
Output elast	0.14 (se=0 .11)	0.04 (se = 0.09)

Notes to table. T statistics in brackets, except in final row. Countries (six) exclude Japan (lacking compositional data). Estimation period: 2020Q1 to 2020Q4. Estimation by random effects, Hausman test on both columns failed to reject null that random effects are preferred.

In both cases, the coefficient on the share $s_H{}^K dk^H$ is negative suggesting that non-dwellings home capital has a lower capital elasticity than dwellings capital, i.e. 1+(-0.56)=0.44, and 1+(-0.88)=0.11 meaning a capital elasticity around one half to one tenth of dwellings capital. The implied output elasticity is one-third of this, see the final row, giving an implied "value" of non-dwellings home capital of about 4-14%, though the standard errors are large. For reference, the output elasticity of business ICT, as

[14] Other country effects, such as skilled labor or human capital, that might affect TFP, should be captured in the fixed effect dummies, as well.

measured by the ICT rental factor share, is around 5% in advanced economies, so, interestingly, the lower estimate suggests a near-equal contribution from home non-dwellings capital.

3 Substitution between workplace and home employment

Substitution from work to home was crucial for the economy to respond to the pandemic quickly, and even as the pandemic has ebbed, there was some return to workplaces. This substitution between home and work may also be important as the pandemic fully recedes to understand and predict, for example, future work patterns. Suppose for example that productivity of home working has risen: does that mean that more will work from home? Standard price theory says not necessarily: if it is hard to substitute work tasks between work and home, then more productive homeworking might reduce working from home. In this section, we treat working from home as an endogenous. We use the experience of the pandemic to estimate the substitutability between work and home, as from the perspective of the firm there were both large changes in labor allocations and exogenous changes in relative prices due to the pandemic. We develop a flexible framework that allows for substitution between capital and labor, home and work, and the presence of relative prices and different technologies.

In this section we rely on UK data, referring to economic conditions and the health data. The latter informed the government response to the pandemic, but economic conditions were also a consideration. We first discuss the course of the pandemic and lockdowns to provide context for the swings in WFH, but it is important to note that we do not identify the WFH effects from these endogenous policy changes. The government announced a national lockdown on March, 23 2020, which came into force on March, 26 until June, 23. Local lockdowns remained in place in some areas, while conditions were eased elsewhere allowing people to return to the workplace and shops and restaurants to reopen, restrictions were tightened from September,22, and a second lockdown came into force on 5 November until 2 December. The uncertainty around these lockdowns is illustrated by an announced intention to allow families to meet in a five-day window over Christmas, subsequently reduced to one day, followed by a third lockdown imposed from January, 6 2021. On February, 22 the government published a roadmap for lifting the lockdown driven by the vaccine rollout and reductions in infections, hospitalisations and deaths. Conditions also varied geographically in England, Wales, Scotland, and Northern Ireland. [15] Our identification strategy does not use these lockdown timings but instead uses the underlying virus and economic data, which is consistent with the arguments and evidence in a number of research findings, suggesting that lockdowns per se did not drive economic choices and

[15] The U.K. lockdown scenarios are summarized in greater detail:
https://www.instituteforgovernment.org.uk/sites/default/files/timeline-lockdown-web.pdf

activity, so much as did the underlying dynamics and risks of the virus. These comparisons are often made comparing nearby locations in the U.S., across states for example, or nearby cities, with similar virus exposures but different policies (Goolsbee and Syverson 2021; Gupta, Simon, and Wing 2020). In such cases, the consistent finding is that behavior changed prior to the lockdowns being put in place or relaxing. We will capture those effects using UK data on spread of the virus and economic conditions.

3.1 What determines the extent of WFH?

We begin with the pre-pandemic position: workers could in principle work from home or at the workplace. Their relative productivity before the pandemic is now a matter of intense research scrutiny and remains unresolved: in some findings productivity is higher e.g. in call centres, some lower e.g. as reported by firms in some industries, and in others it seems to be changing.[16] We develop a framework that can encompass these conflicting findings (following (Katz and Autor 1999; Johnson and Stafford 1998)) and write the production function as

$$Y = \left((1-\beta_H)\left(B_W(K_W^{\alpha}L_W^{1-\alpha})\right)^{(\sigma-1)/\sigma} + \beta_H\left(B_H(K_H^{\alpha}L_H^{1-\alpha})\right)^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)}, \qquad (10)$$

where Y, K and L are output, capital and labor and the subscripts W and H indicate work and home. Turning to the other terms, first, B_w and B_H are "intensive" technical levels/change i.e. change that makes capital and labor better at doing their existing tasks at the workplace or at home (e.g. a computer that runs software can do it both at work and at home and so could represent an increase in both B_w and $B_{H.}$)

Second, β_H represents "extensive" "home-biased" technical change i.e. an increase in β_H is technical change that makes potential capital relatively better at doing the task of workplace capital: e.g. a telecoms network with a video function that enables workers at home to see fellow workers without come to work.

This framework helps interpret the differing empirical evidence. A call center worker, for example, who works at home might be thought of as a worker whose single task is being carried out at home, with relative productivity B_H/B_W. A worker who is part of a team and/or is performing a group of combined tasks faces a relative productivity $\beta_H/(1-\beta_H)$ which might differ depending upon communication technology and might change over time with learning.

Define $a_W \equiv (K/L)_W$ and $a_H \equiv (K/L)_H$ (and assume for the moment these are fixed) the first order conditions are standard (below are those for labour; there is a parallel set for capital)

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[16] (Bloom et al. 2013) find positive effects based on experimental data. Surveys of employees and employers find mixed effects.

$$\frac{L_H}{L_W}=\left(\frac{P_{LH}}{P_{LW}}\right)^{-\sigma}\left(\frac{\beta_H}{1-\beta_H}\right)^{\sigma}\left(\frac{B_H}{B_W}\right)^{\sigma-1}\left(\frac{a_H^{\alpha}}{a_W^{\alpha}}\right)^{\sigma-1}, \tag{11}$$

Before turning to estimating (11), we may use it to examine a number of questions. Starting with the pre-pandemic era there seem to be three facts to explain. First, relatively few people worked from home, i.e. L_H/L_W was low. We emphasise that there was relatively little *market* work at home: in the UK for example, in 1981 the share of adults working mainly at home was about 1.5%, rising to 4.5% in 2019 (Felstead et al, 2020). Second, working from home trends strongly downward over the course of the 20th century in the sense that the number of domestic workers has fallen over time (market worker hours per household fell from eight to one hours per week 1900-1950 in the US (Ramey 2008)).

Third, over that time, it seems likely that the relative "capability" of WFH has risen with more potential capital in the home, perhaps considerably with the widespread adoption of home telephones, home computers and faster internet connections (in 1980 only 72% of UK households had a phone; there was no domestic internet). Yet the relative numbers of WFH have fallen, in the case of domestic workers, or not changed much. Why is this?

Equation (11) gives a remarkable number of insights. Assume first production at home is simply more labour intensive: $a_H/a_W < 1$; if for example, production at home is artisanal i.e. less capital intensive. Can this explain low L_H/L_W? Not necessarily, since with $\sigma < 1$, then equation 11 predicts L_H/L_W would be *higher* (relative to an economy with, say equal K/L at H or W). With little substitution between H and W, economies would need many workers at home to produce the same output.

Second, and related, Equation (11) gives some insight into the importance of the definition of output and the importance of σ. Capital at home, in the sense of connected devices, has been rising strongly as these items become utilities rather than luxury goods or services. If this is a rise in a_H (we consider B_H and β_H below) this can explain a decline in domestic workers at home if those "domestic services" have a low elasticity of substitution between such services located in and outside the home.[17]

Third, if we return to the assumption that K/L is equal at work and home, then we can explain low pre-pandemic L_H/L_W by low B_H and β_H i.e. low relative productivity at home. What then explains the relative stability of this ratio as technologies have presumably improved?[18] The rise in computers has presumably raised B_H but has likely raised B_W as well; that is, it improved the productivity of tasks both at home and the workplace. The rise of networks, communications and mobile is presumably more

[17] Against this, there was a small rise, or at least no decline, in time spent on domestic tasks, typically by women, from around the 1900s to the 1960s, the period of adoption of domestic appliances (an observation referred to as the Cowan puzzle by (Mokyr 2000) after the work by (Cowan 1983), see also (Ramey 2009)). Mokyr argues that the rise in time spent co-incided with a change in time allocation towards providing (perhaps overproviding) more health services at home which are hard to substitute.

[18] We use technologies rather broadly here, noting Katz and Autor's observation that an aggregate production function with two factors reflects a number of forces, for example, the non-neutral effects of changes the relative prices or quantities of non-labor and capital inputs e.g. energy ((Katz and Autor 1999).

akin to a rise in β_H but it seems like networking and communications would raise the relative productivity of all types of "remote-from-premises" working, which would include not only WFH, but outsourcing of the production network more generally, even overseas. Perhaps a case of this is Uber, a new platform allowing those seeking taxi services to match more efficiently with the potential capital at home that can substitute with "vehicle capital": this business has seen a large rise in WFH consistent with a large rise in β_H and/or B_H with $\sigma > 1$.

Finally, it might be argued that working from premises was the pooling equilibrium in a signalling game whereby workers, who had the choice, would signal their unobservable quality by turning up to work (those at home signalled they were low quality). This would explain the reason that WFH is equated with shirking (Barrero, Bloom and Davis, 2020a). If the pandemic has relieved that asymmetric information problem then there might be more WFH, although the position of new starters/job switchers who haven't made a reputation is not clearly improved. An alternative is a collective action problem whereby co-ordinating on all office or all home work are both stable equilibria in a co-ordination game. In both cases however, it would still seem relevant to explore relative productivity and substitution possibilities.

3a. Estimating the elasticity of substitution.

The dynamic version of equation (11) is

$$d\,ln\frac{L_H}{L_W} = -\sigma d\,ln\left(\frac{P_{LH}}{P_{LW}}\right) + \sigma d\,ln\left(\frac{T_H}{T_W}\right), \quad \text{where} \tag{12}$$

$$d\,ln\left(\frac{T_H}{T_W}\right) \equiv \sigma d\,ln\left(\frac{\beta_H}{1-\beta_H}\right) + ((\sigma-1)/\sigma)d\,ln\left(\frac{a_H B_H}{a_W B_W}\right)$$

.

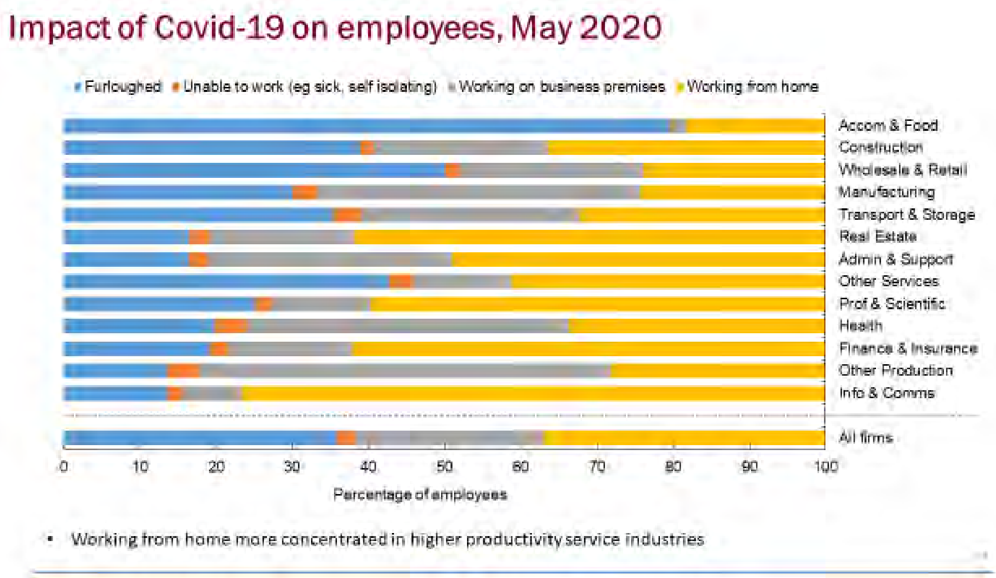
This formulation allows us to read off the elasticity of interest, σ, the elasticity of substitution between work and home, from the relation between changes in (log) relative employment and (log) relative prices, controlling for changes in relative technology denoted, T_H/T_W. This equation can in principle be estimated from the log changes in labor at home and work, with estimates of the relative prices, which we describe below.

Before turning to estimation of the elasticity, however, the pandemic offers a third dimension of job outcomes that bears on the home/premises allocation, namely furlough. Equation (12) suggests that if it becomes costly to employ workers in the workplace, they will be sent home. However, we must allow for the furlough program offered by the UK government during the pandemic, which allowed firms to continue to employ workers, but furlough, rather than lay them off, with the government paying

80 percent of their wages conditional on workers producing no output at all.[19] We will focus on furloughs rather than layoffs, as furloughs were the dominant mode of separations, as evidenced in Figure 6, and layoffs were quite small.

In our framework, furloughs could arise for several reasons. Most importantly, worker to customer contacts are essential to the business of some services, such as food and accommodation, so fixed costs of operating in the pandemic may be very high. Given fixed costs, protection costs per worker may be very high, suggesting a switch to WFH. However, the technological parameters could be unfavorable to working at home (e.g. $\beta_H = 0$, so the productivity of hotel staff WFH is zero). Cases such as these lead to corner solutions in factor choices which confound the first difference specification we propose in equation (12). Hence, we first estimate the determinants of furloughs, essentially taking into account fixed costs and virus exposure, before estimating the location of work.

Figure 6: Covid Impact on Employment By Industrial Sector



Source: Decision Maker Panel survey, Bank of England

We lay out a simple model of fixed operating costs with the choice of WFH or on premises in the appendix. The results are intuitive, implying that firms choose the allocation of labor between home and work depending on the relative productivities and relative costs of home and work production. In addition, though, if the fixed cost of operating is elevated by the pandemic, some firms choose to furlough workers. The option to furlough is more appealing the greater are the fixed costs of operating and the less productive and more costly is labor. These features interact in interesting ways, as suggested in Figure 6, and evidenced in the estimation below. We proxy for the COVID-related fixed cost by vulnerability to virus transmission, as measured by customer and co-worker interactions pre-

[19] Furloughed workers could produce no output under the first lockdown. A later incarnation of the furlough program allowed for workers to be partially furloughed, and when at work they could produce output.

COVID across industries. These fixed industry characteristics are interacted with the severity of the virus over time, measured by *Excess Deaths*. This produces an industry-quarter measure of the exposure of an industry to virus transmission.

3.1 Data

We rely on data on employment by location and furloughs, as well as worker contact data and the costs of working on premises. Our data on employment is industry-quarter, for 2020Q1 to 2021Q1, and comes from the U.K. Decision Maker Panel (DMP): we cannot use official data since it includes as "employed" those on furlough. The DMP also includes survey data, which we discuss below, on the cost of safely equipping employees to work on premises, by industry and quarter. For data on virus risks, we have (cross-section) data from work surveys on the extent to which different industries have different contact (a) worker to worker and (b) customer to worker. These surveys were conducted in France pre-pandemic by epidemiologists to model the potential for disease spread, and we have no reason to think the industry pattern would be different in the UK. We measure the intensity of the virus over time using Excess Deaths. We also utilize data on the (pre-pandemic) capital intensity of the industry, namely its tangible, ICT and intangible intensity.

Starting with the furlough margin, Figure 7 shows for each industry the average furlough/work ratio against the ICT share, tangible capital share and contact with co-workers and customers.

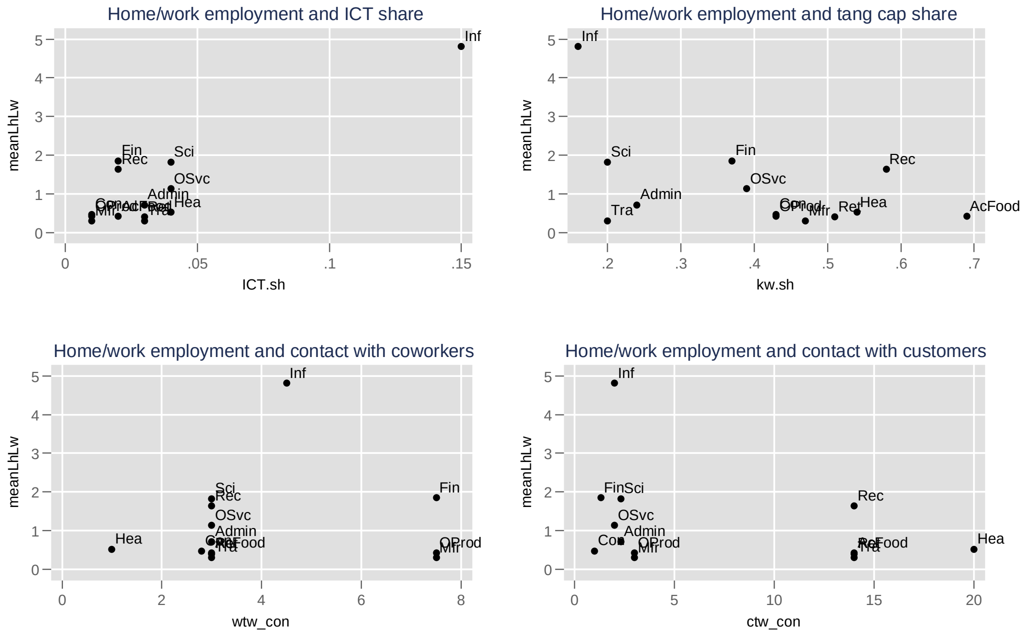
Figure 7: furlough/workplace working and capital shares and contacts

Notes to figure. Figure 7 shows on vertical axis the time-average ratio of workers on furlough to those working at the workplace.

Consider for example recreation and accommodation/food, both of which have had very high furlough rates. These industries have low ICT share, but high tangible capital share. Workers in these industries have low contact with co-workers but high contact with customers. This high contact with customers is consistent with the observation that some industries will have unfavorable technology parameters for WFH, e.g. $\beta_H = 0$ for face-to-face services, suggesting that the relative productivity of work at home in these industries is low. Hence, the pandemic shock means many workers are furloughed in the absence of effective safety protocols at work. Interestingly, these industries have high tangible (physical) capital, consistent with the asset price effects explored by (Favilukis et al. 2020)

Figure 8 shows similar data for the location of work: home/work ratios, capital shares and contacts. The standout industry is information services (newspapers etc) which has very high home/work ratios, high ICT share and low tangible capital share, medium contact with co-workers and little contact with customers. Notice in contrast to the contact risks suggested in Figure 6, the small number of workers at home in accommodation and food.

Figure 8: home/work working and capital shares and contacts



Notes to figure. Figure shows on vertical axis the time-average of workers at home to those working at the workplace.

These data suggest the importance of distinguishing the furlough decision from the location decision. Industries with high face-to-face contacts would in principle benefit from having workers isolate at home, however, the nature of their work (that exposes them to risk) cannot be replicated at home. Hence, as mentioned, the technology parameters can lead to corner solutions for the factor inputs, confounding estimation of substitutability between home and work.

Turning to data on costs, we have survey data from the DMP on the following question: *“"Relative to what would otherwise have happened, what is your best estimate for the impact of measures to contain coronavirus (social distancing, hand washing, masks and other measures) on the average unit costs of your business in each of the following periods?"”* This measures C_W is the relative cost of COVID measures at work. The answers, by industry and quarter, are set out in Figure 9.

Figure 9: COVID-related costs

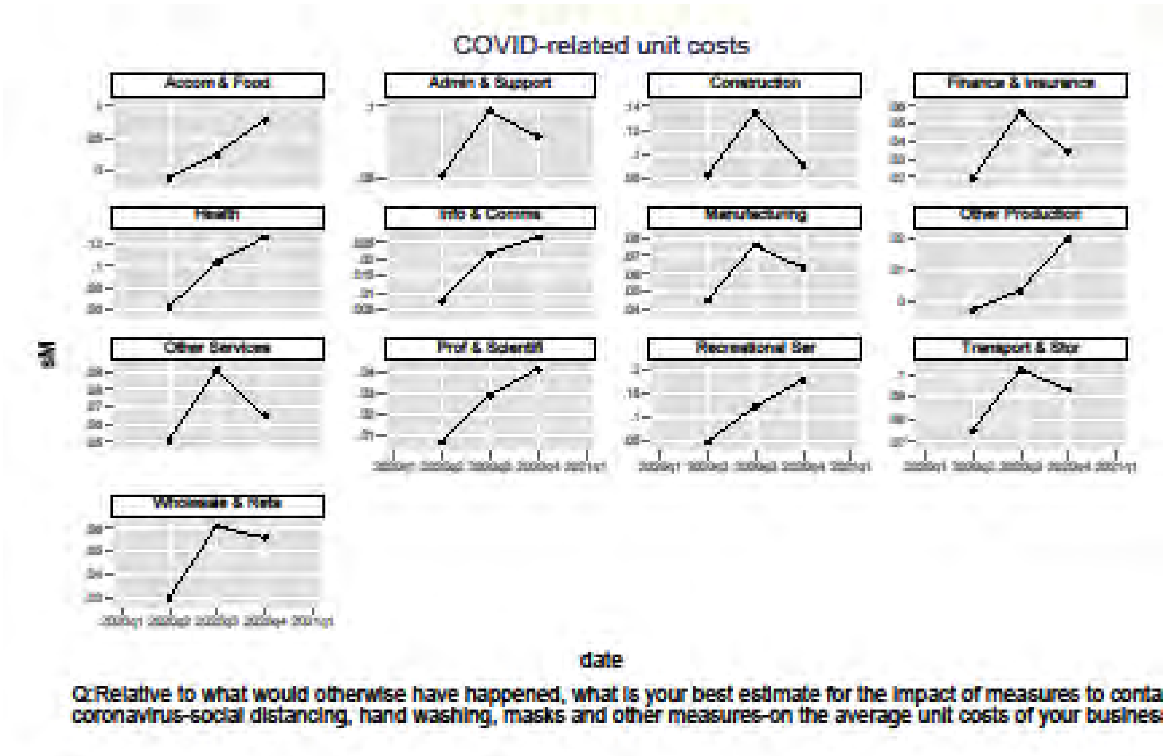


Figure 9 shows that such costs vary by industry and over time, being 3% in wholesale retail and then climbing to 6% before falling to 5.5%. In Recreational Services the figure is above 15% by 2020Q4.

The survey question asks specifically about the cost of physical goods and also about measures such as social distancing. These might include, say the purchase of PPE equipment which has a price and quantity, but it might also include, say, the spacing of tables in a restaurant, extra staff to enforce distancing or the implicit costs of having reduced flows of customers, which has neither price nor quantity. We will interpret such costs as an implicit tax on the use of factors at work relative to home, which in terms of equation (12) would be a rise in P_{LW}. If we suppose the initial costs were P_{LW}^0 then the new costs are $P_{LW} = (1+C_W)\, P_{LW}^0$ so that $\Delta lnP_{LW} = \Delta C_W$ if C_W is small. To relate these changes in costs to relative employment at home/ work and the furlough margin, we measure labor at work using a Cobb-Douglas aggregator of the form

$$L_W = L_{WFW}{}^{s} L_{FUR}{}^{1-s} \quad , \; s = L_{WFW}/(L_{WFW} + L_{FUR}) \tag{13}$$

where L_{WFW} and L_{FUR} are the numbers working from work and furloughed respectively. So L_W takes account of the fact that when it becomes expensive for businesses to cope with Covid, some firms might furlough workers (in which case Lw rises) and not use WFH.

3.2 Estimating Furloughs and Substitution between home and work

To explore this more formally, we first examine the furlough/working from work margin. We estimate

$$\Delta(L_{FUR} / L_{WFW})_{i,t} = \gamma_1 (ICT / K)_i + \gamma_2 (K\_\tan / K)_i$$
$$+\delta_1 (CtoWContact_i * \Delta ExDeath_t) + \delta_2 (WtoWContact_i * \Delta ExDeath_t) + v_t + \varepsilon_{i,t} , \quad (14)$$

where *ExDeath* are excess deaths from COVID that varies by time (not industry) designed to capture the severity of the pandemic. The ICT and Tangible capital shares are intended to capture the technology of work, where ICT enables working from home and Tangible capital is associated with physical workplace infrastructure: both are pre-pandemic measures. Worker contacts are measured separately for customers (*CtoWContacts*) and co-workers (*WtoWContacts*), where we interact with *ExDeath* to capture the risk engendered with contacts at different times during the pandemic.

The results are set out in Table 2. Capital intensity of either type is not significant, but as suggested above, high customer to worker contact industries are associated with high furloughs. We interpret this as a corner solution to equation (11) in which workers are furloughed rather than working from either workplace or home, due to a combination of high risk at work from face-to-face contacts and business constraints of isolating work at home. Technology that might enable either work from home or workplace does not ameliorate this effect, consistent with our interpretation of fixed costs and the nature of face-to-face services. The contact effect is quantitatively large: for industries in which daily customer contacts are 15 (accommodation & food), an increase in excess deaths of 10 percentage points raises the furlough share by 100 percent, while in industries with lower customer contacts of 3 (professional services), the same increase in mortality raises furloughs by 15 percent.[20]

[20] Excess deaths across countries varied widely over the pandemic, as evidenced in https://ourworldindata.org/excess-mortality-covid. In the U.K. first wave, estimates exceed 100 percent, while in the U.S. they reached almost 50% in the first wave and again in January 2021. In our estimation, we use quarterly changes, which dampens some of the extreme values in higher frequency data.

Table 2: Regression estimates of Furloughs
(dependent variable: ΔLfur/Lwfw(i,t))

VARIABLES	(1) ΔLfLw	(2) Δ LfLw
ICT cap share (i)	1.18	
	(0.11)	
Tang capital share(i)	0.40	
	(0.17)	
CtoWcon*ΔExcess death(i,t)	0.41	0.42
	(2.27)	(2.34)
WtoWcon*ΔExcess death(i,t)	0.00	0.00
	(0.00)	(0.01)
Observations	52	52
Number of industries	13	13
Quarter FE	Yes	Yes
Industry FE	No	No

Notes to table. T statistics in brackets. Estimation for the UK, 13 industries over 4 quarters 2020Q1 to 2020Q4. Estimation by random effects. ICT and Tang capital shares measured by industry for t=2018.

For firms that remain open, the relevant decision in this framework is the allocation of labor between the workplace and home. Using the intensive margin and turning to the elasticity of substitution when firms do substitute between production at work and at home, we estimate

$$\begin{aligned}&\Delta\ln(L_H / L_W)_{i,t} = \sigma\Delta(C_W)_{i,t} + \gamma_1(ICT / K)_i + \gamma_2(K\_\tan/ K)_i \\ &+\delta_2(WtoWContact_i * \Delta ExDeath_t) + v_t + \varepsilon_{i,t}\end{aligned} \tag{15}$$

Where the capital/technology and contact variables are as above, and the variable C_W is the relative cost of COVID measures at work, from the survey data described above. Typically, estimates of the elasticity of substitution using relative prices are biased by the endogeneity of wages and potential selection of workers into different types. By using the Covid shock and the additional costs associated with working at the workplace in the pandemic, we obtain plausibly exogenous changes in costs of employment that caused firms and workers to reallocate between premises and home.

To get a sense of the basic correlation, Figure 10 shows a scatter plot of changes in relative home/work employment and cost ratios (controlling for quarter effects, capital and worker contact) for the full four quarters. The downward-sloping curve indicates higher home working with more costly work costs, a negative elasticity.

Figure 10: changes in home/work working and change in COVID costs against

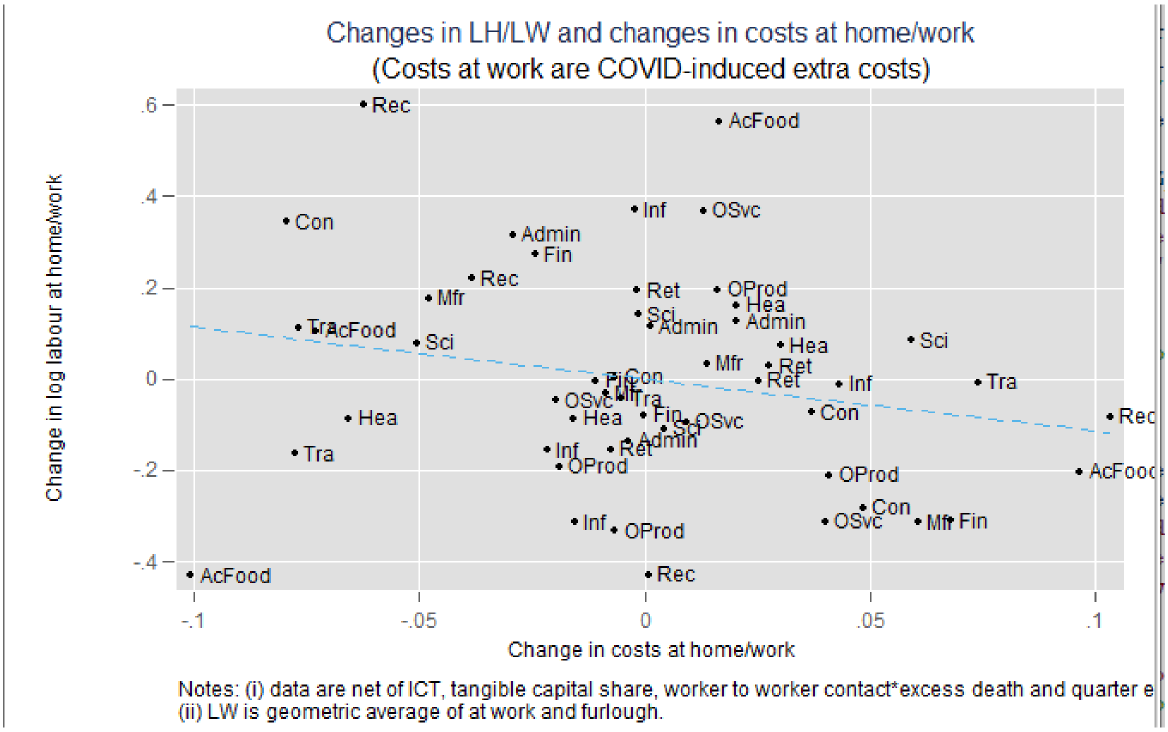


Table 3: Regression estimates of WFH relative to labour at work

(estimates of equation (15), dependent variable: Δ ln(Lh/Lw)

	(1)	(2)	(3)	(4)	(5)	(6)
ΔCosts (i.t)	1.14	1.14	1.95	3.06	3.27	2.18
	(1.58)	(1.60)	(2.53)	(2.50)	(2.66)	(1.99)
ICT cap share (i)	0.93	0.97	1.02	4.42	7.09	2.69
	(0.83)	(1.02)	(1.20)	(2.62)	(1.30)	(1.87)
Tan capital share(i)	-0.02					
	(-0.08)					
WtoWcon*ΔExdeath(i,t)	-0.04	-0.04	-0.01	0.05	0.05	0.03
	(-0.68)	(-0.69)	(-0.24)	(0.59)	(0.58)	(0.38)
Observations	52	52	48	39	36	26
Number of indcode	13	13	12	13	12	13
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No
Quarters				Omit 20Q1	Omit 20Q1	Omit 20Q2
AcFood Ind			No			
Info Ind					No	

Notes to table. T statistics in brackets. Estimation for the UK, 13 industries over 4 quarters 2020Q1 to 2020Q4 except were indicated. Estimation by random effects. ICT and Tang capital shares measured by industry for t=2018. Dependent variable is change in natural log of working from home relative to work labour, where work labour is geometric average of working from work premises and furlough.

The top row of Table 3, which estimates equation 15, shows the estimated values of σ, which range from 1 to above 3 for different time periods and specifications. Columns 1 and 2 are for 2020Q1 to 2021Q1 and include quarter dummies: the point estimate of σ is above 1. Column 3 drops "accommodation and food" given its wide variation shown in figure 7: estimated σ rises. Thus removing the "accommodation and food" industry results in the larger values of the elasticity for the full sample, suggesting that there was little response of WFH in this sector to relative prices, consistent with the low values of WFH in face-to-face services throughout the pandemic.[21] Column 4 drops 2020Q1 on the basis that firms might have learnt better to deal with restrictions and so the dummied out technology parameters might be changing: σ rises again and the ICT share is better determined. Column 5 omits the information industry and column (6) omits 2020Q2 to verify robustness to removing the outlier sector and quarter.

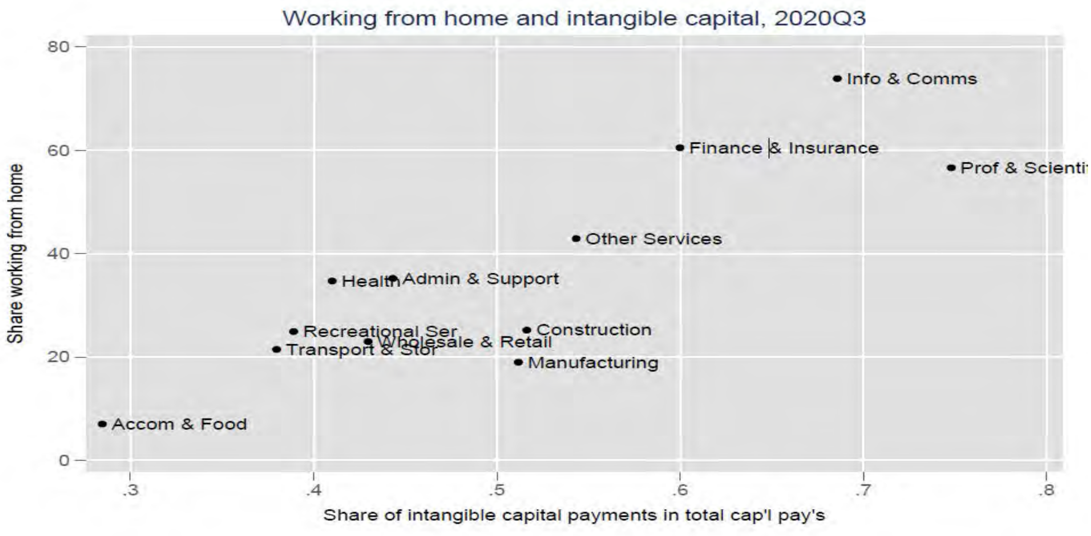
From these different specifications we conclude that technology parameters suggest WFH is associated with high ICT, but there is no impact of tangible capital shares, though the significance (but not the positive effect) for ICT are dependent on the inclusion of the Information Services industry (see column 5) and diminishes in later quarters. These estimates are consistent with the observation that WFH was particularly prominent in professional services, while production industries like manufacturing had intermediate levels of WFH – representing some tasks (administration) which could be done remotely, but others (production) that required proximity to physical capital at the workplace. Using the estimates in Table 3, each percentage point increase in the share of ICT share increases the share of WFH by 1-3 percentage points, with higher values when excluding information services.

In other robustness checks, we dropped the quarter period dummies in case they were obscuring changes in L_H/L_W: σ = 2.82 (t = 3.19). We also interacted the cost changes with quarter dummies and found the best determined and numerically strongest effects were in 2020Q2 and Q3, with a falling off in Q4 and 2021Q1, suggesting possible biases if learning was occurring over the pandemic.

The estimation results suggest a positive relationship, though weak, between *changes* in WFH and the industry's level of intangible capital. Given that the intangible capital value is measured pre-pandemic, we also examine the correlation between an industry's share of employees WFH and its pre-pandemic investment in intangible capital, as shown in Figure 11. The relationship is clearly positive across industries.

[21] Note that after the second quarter, the costs of working at the workplace and the share of workers doing so both rose and fell, so the elasticity is estimated off both positive and negative changes.

Figure 11: Working from Home and Intangible Capital



3.3 The future of working from home?

The estimates in Table 3 provide direct evidence on the substitution from working at the workplace to WFH. There are strong effects of the relative price of working at each location, and also the technology that enables WFH.

To the extent that WFH was motivated by elevated costs of working at the workplace, these costs may well reverse, at least partially, as the pandemic recedes. A large elasticity – ranging from 1 to 3 even in the more proscribed estimation – suggests that WFH may recede along with the costs of working at the workplace. The elasticity is estimated using both positive and negative changes during the pandemic, though a more permanent reversal of costs may have a more durable and potentially larger effect on work location choices, especially if there are frictions associated with changing. Of course, the costs of working from work may not reverse entirely, as customers and workers may demand better ventilation, hand washing, and other health measures going forward.

The technology parameters may have different implications, however. The positive level effect of pre-pandemic ICT on WFH suggests that *existing capacity* to work remotely was crucial to enable substitution, especially early in the pandemic (2020Q2) but also later in the year as the pandemic persisted. This capacity predated the pandemic (the ICT share is measured in 2019) and showed trended growth over time ((Oulton 2012), and hence is unlikely to revert to the pre-pandemic mean. Our interpretation is that the pandemic revealed the capability to WFH that already existed with dwellings capital and connective technologies. The pandemic acted as a large shock and coordination device, overcoming the collective action problem needed to demonstrate the possibility of working remotely. Moreover, the sustained period of the pandemic enabled learning. Both the capacity and the learning will surely continue beyond the pandemic, and, coupled with the suggestion that the elasticity of substitution is greater than unity, this should enabling more persistent WFH, as argued by (Barrero, Bloom, and Davis 2020b).

4 Conclusions

Home capital and home working proved over COVID to be a source of economic resilience. Following one of the largest economic shocks in living memory, our results emphasize the quantitative effects were not as large as they might have been due to the large scale restructuring of production at pace. While these findings are instructive for our understanding of the Covid-19 episode itself, the findings have potentially long-lived implications for production: labor, capital assets, and technology. First, as a growing literature has emphasized, labor dynamics are likely to be deeply moved by the pandemic experience, with profound impacts on distribution. Employees able to work remotely have been advantaged by this shift in production, while face-to-face workers have been laid off or furloughed as safe working was nearly impossible during the pandemic. The correlation between WFH, human capital, and income has been well-documented and reinforces questions about skill development and distribution. Moreover, while we emphasize capital and labor at home, there is nothing in remote work that limits geographies, necessarily. What we observe now as WFH may later manifest more broadly as remote work, from home or elsewhere or abroad.

Second, the pandemic has revealed under-utilized capital across the economy and across the globe. The gig economy previously uncovered and deployed some of this capacity, such as the part-time driver who uses their domestic vehicle for commercial rides. This reflects unused capacity in passenger vehicles, used only 5% of the time (Shoup 2011), or in unused accommodation, rooms, houses, and holiday homes available for rent. Yet, none of these explorations envisioned the deployment of home capital at the scale and speed, with the potential consequences, observed in the context of the Covid-19 crisis. The pandemic revealed unused capacity as a *macroeconomic* phenomenon. While crucial for allowing production to proceed during the pandemic, on-going substitution between home and work reverberates in capital markets. The retail sector was already disrupted by the shift from in-person to online shopping, which was accelerated by the pandemic. To the extent that other goods and services can also be produced from home (not just retailed online) the shift away from business capital will continue and potentially accelerate. Recent work ((Favilukis et al. 2020) and Branzoli, Rainone, and Supino (2021), for example) already documents the lower utilization of business capital, especially structures and real estate, being priced into valuations and rents. This is not necessarily to ring the death knell of urban business centers or their buildings. Even if workers continue to work partially at home, as surveys currently indicate is their preference (DMP, (Barrero, Bloom, Davis and Meyer 2021)), they will still need offices and services at work, and may even demand part-time dwellings in city-centers, if they are commuting from further distances. Production has already been revealed to be surprisingly resilient and flexible when technology allows – one would be surprised if the pandemic was the last chapter in this story.

Third, even if production at home has become more efficient, it is wrong to presume that there will necessarily be more WFH. Where domestic workers became massively more efficient with the advent of domestic appliances, demand for their work fell through the 20th century. Price theory indicates greater WFH when home labour becomes more productive *if* the elasticity of substitution between tasks at home and work exceeds unity. This elasticity is pivotal, and our estimates suggest it does indeed exceed unity, providing more evidence for the likelihood of further remote work.

Finally, the connective technology is crucial. A desk and computer at home has little use for many of the production processes we describe unless it can reliably connect to other workers and their computers. This has been a defining feature of WFH in 2020 and 2021, as compared to earlier, when we might have been using dial-up connection and analog phones. As Mokyr (2001) has stressed, the geographical co-location in the factory helped co-ordinate capital and workers. The modern equivalent of this is networked labor and capital, most recently via the internet. ICT is the enabler, networker and facilitator that makes the connected capital worth more than the capital in isolation. And while platforms that facilitate production and trade (e.g. Amazon) have existed for some time, new examples keep appearing e.g. Etsy, the craft marketplace company in the S&P500. These networks enable companies, marketplaces and facilitators of production and sale from home by unlocking potential capital.

The existence of this technology allowed economic resilience in the pandemic that we estimate accounted for 8 to 14 percent of GDP in the trough of the COVID recession.[22] We have found the shift to work from home is largest in industries which had higher existing stocks of ICT capital, suggesting the important role of investment and technology in facilitating resilience. While the on-going economic impact of new digital technologies has been controversial and difficult to measure, the pandemic may have been the moment that demonstrated the value of this resilience. Future work on more data might take up these important issues.

[22] Excluding Japan, which has even larger values.

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Data appendix:

Data Sources

International Data:

Quarterly data on output (GDP), employed persons and average hours worked are drawn from Eurostat. Energy use to infer the capital used at work is drawn from Eurostat. For Spain we rely on electricity usage data for firms, from (Bover et al. 2020)

Dwellings/residential capital is drawn from National Accounts data.

Google mobility data (for transportation to and from the workplace) is used to infer working from home/office hours for all countries except the UK, where Decision Maker Panel and ONS data are used. The Google mobility data were calibrated to the UK work from home data, where both are available, and then Google mobility is used to estimate work from home for the other countries.

UK Industry Data

Quarterly data for growth in sales revenue and employment split into 13 sectors is drawn from the Decision Maker Panel (DMP), Bank of England. Similarly, we use DMP to derive industry breakdowns of unit costs, employees working from home, working in the workplace, ill or isolating and on government sponsored furlough schemes (employed but doing zero hours of work).

Health and Infection Data

"Excess deaths" is measured from the Oxford University database on excess mortality ((Ritchie et al. 2020; Roser et al. 2020), https://ourworldindata.org/excess-mortality-covid

Contact rates are derived from a survey conducted in 2012 in (Béraud et al. 2015)

The worker-to-worker matrix defines contacts made between workers within a sector, applicable to individuals while at the workplace. The worker-to-consumer matrix is diagonal and defines contacts experienced by workers from consumers within each sector.

These data are also described in (Haw, Forchini, and Christen 2020).

A table of summary statistics for the variables used in the elasticity of substitution regression study is set out below.

Variable	Mean	SD	Max	Min
Dln(home/work& furlough)	0.13	0.39	0.86	-0.65
D(home/work)	0.13	2.78	11.37	-10.96
D(costs of being at work)	0.02	0.06	0.17	-0.11
ICT share	0.03	0.04	0.15	0.01
Capital share	0.4	0.16	0.69	0.16
Worker-worker contact	3.98	2.07	7.5	1
Customer-worker contact	7.15	6.62	20	1
D(excess deaths)	0.04	0.32	0.46	-0.42
Worker-worker contact*D(excess death)	0.17	1.44	3.45	-3.14
Cust-worker contact*D(excess death)	0.31	3.14	9.2	-8.38

Appendix 1: Allowing for fixed costs of production

Static operating condition: operating profits >0,

$$F(K, L, A) - wL - uK - CC(A) > 0 \ ,$$

where in L is (vector) employment and we will think of (vector) K as quasi-fixed for this period (rent, overhead).

Standard optimization requires that the scale of production (*L,K*) be high enough to justify paying the fixed cost, CC, conditional on productivity A. The dependence of the fixed cost on A is useful dynamically so that the fixed cost scales with the size of the firm, but is not necessary in the current setting. This follows from the first-order conditions for K and L that arise from optimizing over the factor inputs in the above.

With COVID, there is both the choice to operate or not, which can send workers to furlough, and also the choice of L at home and at work. For simplicity, we embed normal fixed operating costs in the uK term,and assume that K is quasi-fixed over the course of the pandemic.

During COVID, an additional non-capital fixed costs CC(A) depend on costs of mitigating exposure to the virus. These are fixed costs and not per-worker costs. Per worker costs are measured in c>1, our unit cost measure of workers at work during the pandemic, which would count as a premium on wages in the budget constraint. In practice, we measure the fixed costs using customer to worker contacts and excess deaths – so the interaction of virus exposure by industry and intensity of the virus over time. These fixed costs are avoided by furloughing workers.

Covid thus adds two types of costs to the budget constraint: unit costs which effectively add to wage costs of Lw, and fixed costs of operating (L>0), CC. Allowing for these Covid costs we rewrite

$$F(K, L, A) - w_H L_H - w_W c L_W - uK - CC(A|L > 0) \quad > 0 \ ,$$

First order conditions with respect to L_H and Lw respectively provide

$$F_{Lh}(K, L, A) = w_H$$

$$F_{Lw}(K, L, A) = w_W c$$

To solve the operational decision, solve for the max over two potential modes of operation in the solution:

Hybrid operation: If operate hybrid, pay the fixed CC cost, choose labor at home and at work based on the first order condition, and hire labor if fixed costs are covered.

Furlough: If the fixed costs are too high and/or productivity too low to cover fixed CC and normal operating costs, cease operations and furlough. This is most likely if productivity is low for remote workers, and the cost of premises is high both per unit and in the fixed CC cost. This case leads to a corner solution for employment location, as the first-order condition no longer determines employment allocation.

Appendix 2. Effects of missing capital and labour services contributions.

Recall our main equation

$$
\begin{aligned}
dy = & \frac{\Sigma P_L L}{\Sigma P_Y Y}\left(dl^W + \frac{P_{L_H} L^H}{\Sigma P_L L} d(l^H / l^W) \right) \\
& + \frac{\Sigma P_K K}{\Sigma P_Y Y}\left(dk^W + \frac{P_{K_H} K^H}{\Sigma P_K K} d(k^H / k^W) \right) \\
& + dtfp
\end{aligned}
$$

We measure $L^W = (1 - WFH)H, L^H = (WFH)H$, where WFH is share of the labour force working from home and H total hours worked. For capital we measure $K^W = K^{xD} * E^W, K^H = K^D * PART * WFH$ where K^{xD} and K^D are capital excluding dwellings and dwelings respectively, E^W energy use at work and PART labour force participation. K^{xD} and K^D and PART are assumed constant in our sample. Thus for both capital and labour services we do not use payment weights for home and work, but quantity weights. To get a sense of the possible biases involved, suppose we can write labour services in terms of their heads and "quality" of heads $dl = dn + dq^L$. On the capital side, we have used energy to measure utilisation. thus we can write

$$
\begin{aligned}
dy = & \frac{2}{3}\left(dh^W + \overline{WFH}(dh^H - dh^W) \right) + \frac{1}{3}\left(de^W + \overline{\left(\frac{P_K K^{DWELL}}{\Sigma P_K K} \right)}(de^H - de^W) \right) \\
& + dftp \\
& + \frac{2}{3}\left(q^L + (s^{L*,L^H} - s^{N,N^N})(dh^H - dh^W) \right) + \frac{1}{3}(dk) \\
& \textit{where} \\
s^{L*,L^H} & = \frac{P_{L_H} L^H}{\Sigma P_L L}, s^{N,N^N} = \frac{N^H}{\Sigma N}
\end{aligned}
$$

Thus on the labour side, we have used labour quantities instead of services and labour quantity weights instead of service weights, thus our measured TFP is biased to the extent of (1) omitted quality changes and (2) differences between service and quantity weights. On the capital side, we have used utilisation instead of capital services and hence our measured TFP is biased to the extent of omitted capital services not captured by utilisation.

Regarding capital, the UK ONS produces quarterly capital services esimates (https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/datasets/multifactorproductivityexperimentalestimatesreferencetables) and (https://www.ons.gov.uk/file?uri=%2feconomy%2feconomicoutputandproductivity%2fproductivitymeasures%2fdatasets%2fmultifactorproductivityexperimentalestimatesreferencetables%2fcurrent/050721mfp01unlinked.xlsx), and finds contributions of capital services growth to be very small over the period with quarterly growth rates, in percentage points, starting 202Q1 of 0.1, -0.1. -0.03, 0.03, -0.12 (growth of capital services are almost exactly three times these numbers). This suggests omitted capital services growth, at least for the UK is small.

The contribution of labour composition is 0.45, 1.91, 0.14, -0.06, 0.08. Thus it is much larger in 2020Q2, mostly due to a very large rise in labour composition in arts, entertainment, recreation, which was the sector with the most furloughs (a quarterly rise of 6pppa against a pre-pandemic average change of 0.17pppa)).

There are two additional factors that might bias the results. First, if hours are not well measured. If total hours are measured as average hours per person pre-pandemic times persons, and if average hours per person have fallen over the pandemic, which they have, then total hours are wrong. Second, to measure trends in WFH outside the UK we use outside UK mobility data.