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Revolution in Progress? The Rise of Remote Work in the UK*

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Abstract

The pandemic was accompanied by a wave of adoption of remote work practices. This paper uses online job vacancy data to study how UK firms have adopted remote work. Overall, remote work increased by 300%. Our analysis finds little evidence that occupations have fundamentally changed to better accommodate remote work tasks, nor evidence of changes in the occupational composition of jobs. We find that the overall increase in remote working is driven by the increasing use of remote work at the firm level, especially among firms that were less likely to use remote work before the pandemic. This is consistent with changes in organisational practices or updated information about the viability of large-scale remote working.

JEL codes: J23, J32.
Keywords: vacancies, remote working, pandemic.

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1 Introduction

The Covid-19 pandemic that began in March 2020 was a major shock to the labour market. The widespread implementation of social distancing measures meant that working practices needed to be re-organised at unprecedented speed and scale. Remote working practices were therefore widely adopted across the economy. Firms that needed to adapt necessarily paid the associated financial and organisational fixed costs required for this change.

The adjustment to remote production could have unfolded in a number of ways. First, remote working could have increased on a within-occupation basis so that more tasks associated with a specific occupation became undertaken remotely, i.e., workers employed in occupations that previously had lower rates of remote working would progressively increase the number of tasks performed at home. Second, adjustments could have been made at the between-occupation level such that employers could have changed the composition of their labour demand towards occupations with higher remote-work content or capability. Finally, remote working rates could have increased across the entire workplace at the firm-level, implying firm-specific mechanisms behind remote-work adoption such as changes in organisational practices, updated information about the viability of large-scale remote working, or new general-use remote working technologies.

In this paper, we look at which of these different possible margins of adjustment have driven the substantial expansion of the demand for remote work in the UK since March 2020. When it comes to remote work, our analysis shows a picture of labour market evolution rather than revolution. In the period that we study, higher levels of demand for remote work are occurring through a general increase in the use of remote work at the firm level. We find little evidence of a shift in the 'occupational frontier' of what tasks may be performed remotely within-occupation, and little evidence of a change in the composition of labour demand that would favour occupations more suited to remote production.

Our analysis uses online job vacancy data from the company Burning Glass Technologies (BGT) between April 2019 and March 2021. These data allow us to study firm-level vacancy posting decisions in detail, which allows for an analysis of changes in the composition of labour demand that includes shifts within occupations, across occupations, and at the level of the entire firm. We use these data to construct an indicator of remote work demand by computing the occurrence of remote work related keywords within the text of job vacancy adverts as posted online. This analysis is supported by a manual validation process to ensure that job adverts are accurately labelled as having remote work content or not. Evidence of the robustness of our vacancy-based remote work measure comes from its high correlation with survey-based measures of the use of remote work in filled jobs from the UK's Office for National Statistics (ONS), indicating that our measure provides a good picture of remote work trends and does not just reflect the trends that apply to newly hired staff.

Our analysis is motivated by a conceptual framework which recognises that firms have three margins of adjustment to deal with the Covid shock: they can change the mix of labour inputs towards occupations with a higher remote-work potential (we define remote-work potential in the next paragraph); they can make occupation-specific investments in remote working; or, finally, they can deploy remote working across all occupations. Firms' choices will depend on the cost structure of remote working adoption, particularly whether there are initial fixed costs of adopting remote working technology, to what extent costs become convex if at least some tasks must be performed on site, and whether these costs can be pooled at the firm level or are occupation-specific.[1]

To study the importance of these mechanisms, we consider the vacancy data at different levels of aggregation. We start with an occupation-level analysis of the within-occupation frequency of remote work vacancies and its relationship to intrinsic feasibility. The feasibility measure we use will be referred to hereafter as the 'HLR score' and is developed in Hensvik et al. (2020). It measures the average share of daily hours worked at home in each 4-digit occupation, as declared by respondents to the US *American Time Use Survey 2011–2018*. This measure provides an indicator of the pre-pandemic occupational 'frontier' of remote work; that is, how remote work was spread across occupations based on the perceived costs and preferences of both workers and employers in the period before the pandemic.

A key finding of our analysis is that there has only been a minimal shift in the pattern of adoption of remote work on the occupational frontier. We make this claim because the HLR feasibility measure is able to explain occupation-level patterns in the growth of remote work, and the only limited increases in remote work adoption that are not explained by this measure occur for Administrative and Sales occupations.

In light of these results, a second key part of our analysis studies how the occupation-level remote-work feasibility has affected firms' ability to respond to the pandemic. For this, we estimate a difference-in-differences (DiD) model that compares the evolution of vacancies mentioning remote work across two groups of firms that had respectively a low and high remote-work potential pre-pandemic. This classification is based on the occupational composition of firms' vacancies and the occupation-specific HLR score. The results of this firm-level analysis reveal some evidence

[1] Of course, firms could also react to the Covid shock by cutting production and overall labour demand, and some did do this at the beginning of the pandemic as documented by Forsythe et al. (2020). We will also provide evidence of a drop in labour demand in the UK context. However, our analysis will focus on firms that kept hiring throughout the pandemic.

of 'catching up' by low potential firms. In other words, we see that both firms with high and low-remote work potential according to the HLR score increased their remote-work opportunities by more than 7 times compared to pre-pandemic level. However, the number of vacancies discussing remote work at low potential firms increased faster than what would have been expected based on those firms' occupational structure and established patterns of remote work.

These results motivate a decomposition analysis of firm-occupation data to distinguish the contribution of, respectively, occupation, firm, and compositional factors to the growth of remote work in job vacancies. Based on this decomposition, we are able to rule out a primary role for occupation and compositional effects in driving the increase in remote work in vacancies. Neither occupational fixed effects nor the occupational structure of firms in the post-pandemic period explain the increase observed in remote working as measured in job vacancy data. Instead, the expansion of remote work has been achieved through an increase in firm-specific propensities to use remote work–and this increase affects all types of occupations present within a firm.

There is a large literature on remote and alternative work arrangements, especially since the pandemic (Althoff et al. 2021, Barrero et al. 2021, Bloom et al. 2021, Gibbs et al. 2021, Adams-Prassl et al. 2020b, Bai et al. 2020, Bamieh and Ziegler 2020, Dingel and Neiman 2020, Etheridge et al. 2020, Hensvik et al. 2020, Mas and Pallais 2017, Bloom et al. 2015). Our results showing limited between and within occupational reallocation in the face of very significant changes in working practices are compatible with a model, as per Barrero et al. (2021), where the adoption of remote work before the pandemic was impeded by co-ordination costs and imperfect knowledge about the payoffs of the technology given pre-existing production arrangements. As firms have been forced to experiment with remote working, their propensity to invest in this new technology has rapidly increased, driving the observed surge in remote-work opportunities even in those firms with a low pre-pandemic remote-work potential. As such, these results suggests that the pandemic has in part worked as equaliser of remote-work opportunities across firms. However, our results do not exclude that reallocation dynamics will become important in the future as remote working practices continue to diffuse.

The paper proceeds as follows: Section 3 describes in detail the data sources used in our analysis; Section 4 presents the difference-in-differences results and the decomposition exercise; Section 5 offers a discussion of our findings and their implications for the labour market; and Section 6 concludes.

2 Conceptual Framework

As each work occupation involves a different mix of tasks and different degrees of human interaction, the need for remote working prompted by the Covid crisis will have affected some occupations more than others. The first way firms can deal with the shock is by cutting production, thereby reducing demand for all inputs, as documented by Forsythe et al. (2020) for the USA. Appendix Figure A1 shows that this happened in the UK as well, though only temporarily. Because of the very short-run nature of the reduction in demand, this paper will not focus on this margin of adjustment but instead on the other actions firms took to respond to the Covid shock: namely firms choosing to modify their mix of labour inputs. Whether the most affected occupations will be reduced or not relative to the others depends on the production function, and in particular on the (short-term) elasticity of substitution between inputs.

We consider remote working as a way firms can mitigate output losses happening in a given occupation. Increasing the share of workers that work remotely in a given firm and occupation is costly. These costs are possibly non-linear. Barrero et al. (2021) use the presence of fixed costs as a barrier to the adoption of remote working; these fixed costs may be due to the need to invest in technological tools, train staff, or even overcome psychological barriers (including inaccurate beliefs about the propensity for workers to shirk while working remotely). These costs may also be partly convex, if at least some tasks involving workers in a given occupation must be performed on site. Also key is the extent to which these costs can be pooled at the firm level or are instead occupation-specific. There are two polar cases: if costs are paid once and for all at the firm level, regardless of occupation-specific factors, firms might be more inclined to deploy remote working across occupations. On the contrary, if remote-work technologies are essentially occupation-specific, the adoption of remote working may remain siloed within certain occupations within companies.

While we are not able to observe the cost structure of remote working adoption, in the remainder of the paper we exploit BGT data to provide evidence about the extent to which:

- occupations that were lagging behind in terms of remote work caught up during the crisis;
- firms that were using more remote work before the crisis tended to double down, or were caught up by firms that were initially lagging behind; and
- companies changed the occupational mix of their labour force.

We now analyse each of these possibilities in turn.

3 Data

3.1 Burning Glass Technologies (BGT) Online Job Vacancies

Our core dataset is the UK online job vacancies information collected by the company Burning Glass Technologies (BGT). BGT is a well-known vendor of online job vacancy information for both commercial and academic use. They webscrape information across online sources and de-duplicate entries in order to capture the universe of vacancies in a given country as comprehensively as possible. An increasing number of academic studies use the BGT data to study different aspects of the labor market (Adams-Prassl et al. 2020a, Azar et al. 2020; Deming and Noray 2020; Deming and Kahn 2018, Duchini et al. 2022).

We use UK BGT data from April 2019 to March 2021, comprising approximately 13.5 million vacancies in total. Over this period of time, the name of the firm or organisation posting a vacancy can be directly identified for 47% of all vacancies. We therefore use all of the vacancies to construct aggregate and occupation-level datasets but we are restricted to the 47% subset when doing firm-level analysis.[2]

Firms are defined according to strings that report employer's names and are provided as a data field by BGT. These names include both public and private sector organisations, as well as non-profits – in effect, any organisation that posts job advertisements. BGT also provide an occupational code for each job vacancy and these follow the UK 4-digit SOC 2010 classification. Over our period of analysis, we have more than $265,000$ distinct firms and 369 distinct SOC occupation codes. Below, we define the samples used in the firm-quarter and firm-occupation-year analyses.

[2] Duchini et al. (2022) show that the industry distribution of this restricted sample matches the ONS Vacancy Survey well, mitigating concerns about representativeness.

3.2 Measuring Remote Work Practices via Job Ad Text

In order to classify vacancies as offering remote work opportunities, we identify 18 keywords and phrases that signal remote work, including 'work from home', 'home-based' , 'tele-commuting', and 'virtual job'. Following Duchini et al. (2022), we collate these terms from sources such as Timewise, a website posting vacancies with flexible work arrangements, and ACAS, the Advisory, Conciliation and Arbitration Service (ACAS 2015), an independent public body offering services to improve workplace relations. We further integrate these terms with manual classifications with the aid of research assistants. As a result, a given vacancy is classified as being remote if at least one of these keywords or phrases is used in the advertisement.

Appendix Figure A2 shows the frequency of these terms, which are organised into three clusters reflecting different types of remote work terms. The first cluster captures terms relevant to home based work and is the largest. The second and third clusters cover terms related to remote working and teleworking respectively. As a robustness check on the quality of the classification algorithm, we manually audit a sample of eight hundred job vacancies. Based on this sample, our algorithm correctly classifies job vacancies as offering remote working 95% of the time. Among those job ads that are misclassified, one third are false positives and two thirds false negatives.

In Figure 1, we plot the time trend in the share of vacancies offering remote work based on our text-based measure. This shows a considerable rise in remote work vacancies, with the level rising from 2.5% before the pandemic to 8% in early 2021 (during the second national lockdown in the UK). One potential issue with our measure is the extent to which it reflects changes to firms' workforce and labour demand in general versus reflecting only what is happening with new hires (i.e., only reflecting what is happening to labour demand at the margin).

To investigate this, we compare our vacancy-based measure to survey-based measures of remote working from the ONS 'Opinion and Lifestyle' (OPN) survey. This is a weekly survey conducted over the course of the pandemic that explicitly asks employed individuals whether they were working at home for part or all of the time. Appendix Figure B1(a) plots the relationship between the two measures using month-SOC2 observations. There is a strong correlation of 0.75, suggesting that the way a firm discusses remote working in their job advertisements does reflect the picture for the workforce within that firm.

However, one point to note here is that the *levels* of these measures are quite different: the unweighted mean remote work share across $N = 300$ observations is 0.227 according to the OPN and 0.054 for the text-based vacancy measure. This is likely to be a result of under-reporting of remote work options within job advertisements, for example because some remote working is implicitly assumed to be a part of some jobs. As a window into this we look at SOC1-level differences in the two measures. Appendix Figure B1(b) plots the coefficient estimates for regressions of the occupation-level difference in the measures on SOC1 dummies. This shows that the differences do follow the pattern of being larger in managerial, professional and associate professional occupations (for which it may be assumed that home working is more common and more possible), but smaller in manual occupations (where the opposite assumption applies).

In Section 5, we provide further discussion of this representativeness and how it might affect our results; but the strong correlation of 0.75–0.82 with the OPN survey-based measure suggests that our vacancy measure is a credible indicator of firm-level patterns in the use of remote work.

3.3 Remote Work Feasibility Measures

We proxy the *ex ante* remote work feasibility or potential for remote work using the occupation-level measure developed by Hensvik et al. (2020) that we call the 'HLR' measure. This is derived from the US *American Time Use Survey 2011–2018* and counts the average number of work hours performed at home by individuals employed in a given occupation. As such, it is a measure of remote work feasibility based on pre-pandemic work practices.

Appendix Figure B2 relates our text-based measure of actual remote work vacancies to the HLR hours-based measure of remote work feasibility: 4-digit occupations with a higher HLR score have also a larger share of vacancies mentioning remote work opportunities both pre- (Panel a) and post- (Panel b) pandemic, though this correlation strengthens from 0.33 to 0.41 after the Covid-19 outbreak. We refer to this shift again later in our formal occupation-level analysis.

4 Empirical Models and Results

4.1 Occupation-Level Analysis

We would like to understand the extent to which the increase in remote-working has followed pre-crisis trends. Did occupations with greater pre-crisis remote-work potential see a higher increase in remote-work share during the pandemic?

To explore this aspect, we regress our text-based remote work indicator on the HLR hours-based measure of remote work feasibility. The overall within-occupation increase in remote work will have some component that is due to inherent remote work feasibility, and another, second component that can be attributed either to other occupational characteristics or to structural changes in feasibility. We estimate the following regression:

$$\Delta RWShare_j = \alpha + \beta \cdot HLR_j + \phi_l \cdot soc_l + \varepsilon_{jt} \tag{1}$$

where $\Delta RWShare_{jt}$ represents the change in the share of remote work vacancies in each 4-digit occupation j between the pre- and post-pandemic period, and ε_{jt} is an error term. Our variables of interest are the occupation j HLR score and 1-digit occupation fixed effects ϕ_l (where l is the 1-digit occupation corresponding to 4-digit occupation j, and managerial professions are the excluded category). The latter fixed effects provide a measure of the SOC1 variation that exists even after controlling for inherent remote work feasibility. In turn, this provides an indicator of where there may have been structural changes in remote work feasibility as a result of the pandemic.

The estimates are reported in Figure 2(a). The HLR variable is strongly correlated with the change in the within-occupation remote work share. An increase of the HLR value by 10 percentage points (the HLR mean is equal to 15%) is associated with a 0.8 percentage point increase in the remote-work vacancy share.[3] The conditional estimates of the SOC1 fixed effects show that the growth experienced in the Sales and Administrative groups was higher than that of more inherently remote-friendly occupations such as professionals and Associate Professionals.[4]

In Figure 2(b) we show the results of estimating a version of equation (1) with the overall vacancy shares for 4-digit occupation j at time t as the dependent variable. This provides a test of whether remote work feasibility affected labour demand

[3]In terms of explanatory power, this HLR-inclusive model has an adjusted R^2 of 0.271 versus 0.221 for a model that only uses the SOC1 fixed effects.

[4]While all occupations saw an increase in the offer of remote work opportunities, administrative and sales professions experience the largest rise, with the share of remote work vacancies being respectively 4.5 and 3.5 times higher in 2021 compared to 2020 (Figure B3).

with, for example, low feasibility occupations declining in their vacancy shares relative to high feasibility occupations. While Figure 2(b) indicates that there were significant reductions in labour demand in some occupations (e.g., Sales) there is no evidence of a compositional shift explicitly linked to remote work feasibility.[5] This holds for alternative specifications such as unconditional models or different functional forms.[6]

In summary, our occupation-level analysis suggests that there was no significant pattern of between-occupation substitution in labour demand based on remote work feasibility. Instead of between-occupation effects, our occupation-level analysis shows that there was a widespread within-occupation increase in remote work but that this increase was in line with pre-pandemic patterns of remote work feasibility.

4.2 Did firms with lower remote-work potential catch up during the pandemic?

4.2.1 Empirical strategy

How did the occupation-level changes in remote working translate to the firm level? To investigate this, we posit a difference-in-differences model centred on a firm-level measure of pre-pandemic remote work potential. Appendix Section C describes the sample used for this analysis in detail. The pre-pandemic remote work potential measure combines information on each firm's occupational composition (as available in the vacancies data) and the HLR score:

[5]The decline in demand in occupational groups such as Sales fell can be explained by policy changes specific to these occupations (e.g., the closure of stores and restaurants).

[6]For example, the HLR estimates for an unconditional model that omits the SOC1 dummies is 0.0005 (0.0005). And the HLR estimates for models using log vacancies as the dependent variable are -0.080 (0.146) (conditional) and -0.047(0.142) (unconditional).

$$RWPotential_k = \sum_j (ShareVacs_{jk} * HLR_j) \quad (2)$$

To perform this estimation, we first calculate the share of occupation j in firm k in the baseline year 2020[7], denoted as $ShareVacs_{jk}$, and then multiply this by the occupation-specific HLR score HLR_j. We then sum these products across all the J occupations represented in the firm during the baseline period to get a vacancy-weighted measure of the extent to which a firm's employees can work remotely. The cross-firm distribution of this remote work potential measure is shown in Figure C1 and indicates that the median value is approximately 0.2. Since this measure is a weighted index, it can be interpreted as saying that 20% of the total hours worked at a median firm can be done remotely. We can then split firms into two groups according to different thresholds of $RWPotential_k$ and compare their evolution in the posting of remote work vacancies in a difference-in-differences framekwork.

Our main model is based on a sample split at the median. Appendix Table C2 compares the pre-pandemic characteristics of the resulting high and low remote work potential firms. By construction, high remote work potential firms had a larger share of working hours that can be performed at home (27% against 14%). Moreover, the high group posted fewer vacancies on average (83 versus 193), but a higher share of them is for what we define as 'highly-remotable' occupations, i.e., professions with a HLR score above the median score across 4-digit occupations. In terms of the industry distribution, the high group is relatively less concentrated in Public Administration, Education and Health.

Since our main outcome of interest – the number of vacancies mentioning remote

[7]Note that we drop observations from March 2020 when constructing this measure.

working – is a non-negative integer with a high proportion of zero values, we make use of a Poisson regression model. Specifically, we assume that this outcome follows a Poisson distribution, and model the mean for firm k in quarter q as follows:

$$\mathbb{E}\left(Y_{kq}\right) = V_{kq} * \exp\left[\alpha_k + \theta_q + \pi\left(LowRWpot_k * Post_q\right)\right], \tag{3}$$

where Y_{kq} is the number of remote work vacancies posted by firm k in quarter q, and V_{kq} is the total number of vacancies posted by firm k in quarter q. The terms α_k and θ_q are employer and quarter fixed effects respectively. $LowRWpot_k$ is a dummy equal to 1 if the employer is a low remote work-potential firm as defined above, and $Post_q$ is a dummy for quarters between April-June 2020 and January-March 2021. Conditional on the validity of the difference-in-differences strategy, a positive estimate of π would suggest that the pandemic pushed low potential firms to 'catch up' with high potential ones, while a negative π would imply a widening of the gap between the two groups in the pandemic period.

4.2.2 Results

In Figure 3(a), we display the evolution over time of the ratio of remote-work vacancies over the total number of vacancies posted by firms with low vs. high remote-work potential. We show that both groups experience large increases in this variable after the Covid-19 outbreak. Another striking fact is that low-potential firms seems to have caught up in relative terms: in the quarter before the crisis, high-potential firms posted remote-work vacancies twice as often as low-potential ones (10% vs. 5%). In the first quarter of 2021, high-potential firms were posting remote-work vacancies only 35% more often (31% vs. 23%).

Our regression analysis allows us to quantify this catch-up effect, conditional on firm and time effects. We illustrate these results in Figure 3(b), which presents the event-study analogue of regression 3. Here leads and lags of an interaction with $LowRWpot_k$ are estimated relative to the last pre-outbreak quarter, Q1 2020, and the vertical blue line refers to the start of the pandemic. In line with the evidence presented in Figure 3(a), the positive and significant estimates for the post-pandemic interaction terms confirm the presence of a catch-up effect, with the pre-pandemic terms showing only limited evidence of differential pre-trends across the two groups.

Table 1 presents the corresponding difference-in-differences estimates. In Column 1, we use our main definition of low remote work potential firms as those with a pre-pandemic remote work potential below the median across employers. In line with the dynamics seen in the event study, these estimates indicate that the low group expands the offer of remote work opportunities by 15% more than high-potential ones in the pandemic period. This corresponds to closing 15% of the pre-pandemic remote work offer gap.

Results presented in column (2) explore the heterogeneity of previous results with respect to the initial remote-work potential. We split firms into quintiles, and interact quintile dummies (omitting firms with the largest remote work potential as the category of reference) with the $Post_q$ dummy. We show that firms between the 20th and 40th percentiles of remote-work potential are those that catching up fastest, increasing the share of remote work vacancies by 32.6% more than firms in the upper quintile. In contrast, we cannot reject that firms in other quintiles (including those in the bottom quintile) expand remote-work opportunities at the same speed as those in the top quintile.

The occupation-level analysis indicated that pre-pandemic remote work feasibility was a good predictor of the expansion of remote work vacancies during the pandemic. The difference-in-differences analysis confirms that firms with a higher pre-pandemic remote work-potential maintain a higher ability to offer remote work opportunities relative to low remote work-potential firms. At the same time, the pandemic acts in part as an equaliser of remote-work opportunities across firms, as low remote work-potential firms close part of their pre-pandemic gap in remote-work vacancies.

4.3 Disentangling firm-specific from occupation-specific channel in remote-work adjustments

This section sheds light on the channels through which firms increase their remote work offering. We perform a firm-occupation level analysis to study the expansion of firm-year remote working rates and its drivers. Appendix Section C describes in detail the sample used for this analysis.

We consider the number of vacancies with remote-work content Y_{jkt} offered by firm k in occupation j during year t. We assume that Y_{jkt} is distributed as a Poisson with latent parameter $\lambda_{jkt} = V_{jkt} \exp(s_{jkt})$, where V_{jkt} is the total number of vacancies posted by firm k in occupation j in year t, and the latent s_{jkt} can be decomposed into three terms:

$$s_{jkt} = \beta_t + \alpha_{kt} + \gamma_{jt}$$

where α_{kt} is a firm-year specific propensity for remote work, γ_{jt} is an occupation-year specific propensity for remote work, β_t is the log of the average share of vacancies with remote-work content in year t (α and γ are normalised to average to zero within each year). We fit a Poisson model of Y_{jkt} introducing the log number of vacancies V_{jkt} with a coefficient constrained to one. We obtain the estimates $\hat{\beta}_t$, $\hat{\alpha}_{kt}$ and $\hat{\gamma}_{jt}$ from this model. Using these, we can define the predicted remote work rate for the average vacancy posted by firm k in year t:

$$\hat{\lambda}_{kt} = \sum_j \frac{V_{jkt}}{\sum_{j'} V_{j'kt}} \exp(\hat{\beta}_t + \hat{\alpha}_{kt} + \hat{\gamma}_{jt})$$

The rate is obtained by dividing the expected number of remote-workable vacancies in firm k in year t $\left(\sum_j V_{jkt} exp(\hat{\beta}_t + \hat{\alpha}_{kt} + \hat{\gamma}_{jt}) \right)$ by the total number of vacancies posted by firm k in year t $\left(\sum_{j'} V_{j'kt} \right)$. The term $\frac{V_{jkt}}{\sum_{j'} V_{j'kt}}$ can be interpreted as the share of vacancies in occupation j within firm k. This will allow us to track compositional changes in firms, specifically those that could reflect substitution between occupations with low versus high remote work feasibility.

This formulation for predicted remote work rates can then be used to trace the evolution of remote working between two years 0 and 1 in firm k according to several channels:

i) Even adoption across firms and occupations: remote work could have become more or less likely for all firms or occupations at the same time without any structural imbalance. In this case, only β_t moves between year 0 and year 1.

ii) Occupation-specific change: even within the same firms, some occupations might have seen the share of remote-workable jobs increase more than others. In this case, the occupation effect γ_{jt} would have moved between the two years.

iii) Change in occupation composition: firms could have changed the portfolio of vacancies they put forward, and this may have been biased according to intrinsic remote work content. This could happen even when the remote-work content of occupations does not change. Within our notation, this effect will show up in relation to the occupational share term $\frac{V_{jkt}}{\sum_{j'} V_{j'kt}}$.

iv) Firm-specific adoption: firms could be asymmetric in the way they offer remote work, even if they posted the same portfolio of vacancies. In this case, the α_{kt} firm effect will move between years 0 and 1.

We distinguish which of these phenomena are driving the change between the pre-covid firm-level predicted remote work rate ($\hat{\lambda}_{k,0}$) and post-covid predicted firm-level remote work rate ($\hat{\lambda}_{k,1}$) by building the following counterfactuals:

$$\begin{aligned}
\tilde{\lambda}^{o}_{k,1} &= \sum_j \frac{V_{jk0}}{\sum_{j'} V_{j'k0}} \exp(\hat{\beta}_0 + \hat{\alpha}_{k0} + \hat{\gamma}_{j1}) \\
\tilde{\lambda}^{o,c}_{k,1} &= \sum_j \frac{V_{jk1}}{\sum_{j'} V_{j'k1}} \exp(\hat{\beta}_0 + \hat{\alpha}_{k0} + \hat{\gamma}_{j1}) \\
\tilde{\lambda}^{o,c,f}_{k,1} &= \sum_j \frac{V_{jk1}}{\sum_{j'} V_{j'k1}} \exp(\hat{\beta}_0 + \hat{\alpha}_{k1} + \hat{\gamma}_{j1})
\end{aligned}$$

The first counterfactual $\tilde{\lambda}_{k0}$ only allows the occupation-specific effect $\hat{\gamma}_{j0}$ to vary between periods 0 and 1. The next $\tilde{\lambda}^{o,c}_{k,1}$ counterfactual then allows the occupational composition term to also vary. This is denoted changing the subscript in $\frac{V_{jkt}}{\sum_{j'} V_{j'kt}}$ to 1 and effectively means that we are 'plugging in' the post-Covid occupation shares into our calculation. Finally, in $\tilde{\lambda}^{o,c,f}_{k,1}$ we also allow for variation in the firm effect $\hat{\gamma}_{jt}$. Note that we build these counterfactuals up iteratively such that they add occupation, compositional and firm effects on top of each other in succession.

Figure 4 displays a series of binscatters where the pre-covid firm-level predicted remote-work rate ($\hat{\lambda}_{k,0}$) is on the x-axis and counterfactuals $\tilde{\lambda}^{o}_{k,1}, \tilde{\lambda}^{o,c}_{k,1}, \tilde{\lambda}^{o,c,f}_{k,1}$ are on the y-axis. Panel (i) here shows what are effectively the 'actual' pre and post remote work rates where the time, occupation and firm components are all allowed to vary across the two time periods. The fact that the blue mass of observations in the lower half of the panel is above the 45 degree line implies that the predicted RW rate increased more in firms with a low pre-pandemic RW rate.

The next three panels of Figure 4 present counterfactuals based on varying different components. In panel (ii) the orange mass represents a plot of the $\tilde{\lambda}^{o}_{k,1}$ occupation counterfactual against the pre-pandemic RW rate $\hat{\lambda}_{k,0}$. This mass closely follows the 45 degree line indicating that occupation effects cannot explain much of the shift in the predicted RW rate. Panel (iii) then plots $\tilde{\lambda}^{o,c}_{k,1}$ on the y-axis, thereby adding in the occupational composition term and giving a new green mass of predicted RW rates. Again, this closely follows the 45 degree line and points to a very limited role for compositional shifts. In the final panel (iv) we plot $\tilde{\lambda}^{o,c,f}_{k,1}$ and add in the firm effects. This results in a purple mass that is parallel to the original blue mass of 'actual' pre and post Covid predicted RW rates. Overall, this implies that the slope relating the pre and post rates is determined by the firm effects rather than occupation or compositional effects. Note finally that the gap between the purple and blue masses in panel (iv) is representative of the common time effect $\hat{\beta}_t$.

The decomposition shows the primary role of the the firm-specific component, which seems to have evolved in an asymmetric manner across firms over the two periods. Our decomposition is able to rule out a shift in occupation effects in terms of how they reflect intrinsic remote work flexibility. It is also able to rule out a major shift in the occupational composition of firms toward more remote feasible occupations. Instead, the expansion of remote work was achieved through an increase in firm-specific propensities to use remote work, with this increase affecting all types of occupations present in a firm.

5 Discussion

Both the DiD model and the decomposition analysis show a pattern of catch-up in the offer of remote-work opportunities from firms that were less likely to employ this practice pre-pandemic. To further qualify these results, it is worth reconsidering which firms we use in each analysis. As explained in section 3, the DiD analysis uses both firms that were not posting any remote-work vacancy before the pandemic and only start doing it afterwards, and firms that were already posting some remote-work vacancies and increase the intensity of this remote-work offer after the Covid-19 outbreak. We call the former extensive-margin firms and the latter intensive-margin employers. In contrast, the decomposition analysis only uses intensive-margin firms as employers need to post at least one remote-work vacancy in each year to contribute to the estimation of yearly predicted remote-work rates.

Appendix Table C3 shows that when estimating the DiD model on the decomposition sample, the point estimates are very similar to those obtained using the main DiD sample, though less precisely estimated. In contrast, there is no sign of a catch-up effect when using only the extensive-margin firms in the DiD sample. In other words, this comparison suggests that among low-potential firms, those who were already offering some remote-work opportunities drive the catch-up effect.

6 Conclusion

The pandemic has been accompanied by a massive wave of adoption of remote practices. This paper studies the mechanisms that have underpinned this process using online vacancy data for the UK. Our empirical results show that firms which were using remote work to a lower extent (or which used more occupations that looked more difficult to adjust to remote working) before the pandemic are more likely to catch up in the aftermath of the crisis. Adjustments seemed to take place at the level of the entire workplace rather than at the occupation level (across firms) or tweaking labour demand towards occupations with higher remote-work content.

These results spur further questions. First, it will be important to identify where low and high-potential firms operate in the UK to study the implications of this catch-up effect for the geographic location of job opportunities. In particular, by removing the geographic boundaries that usually constrain individuals' work choices, remote working may reduce firms' local monopsony power (Barrero et al. 2021). Second, and related to the first point, if we consider remote working as a job amenity, the diffusion of this work practice has ambiguous consequences for employees' wages. On the one hand, workers may more be willing to accept lower wages to avoid commuting to work (Mas and Pallais 2017). On the other hand, the large investment in remote-working technologies that firms have undertaken may lower its organisational costs, limiting any wage penalty associated with this work arrangement (Barrero et al. 2021). Addressing these policy-relevant questions is an important avenue for future research.

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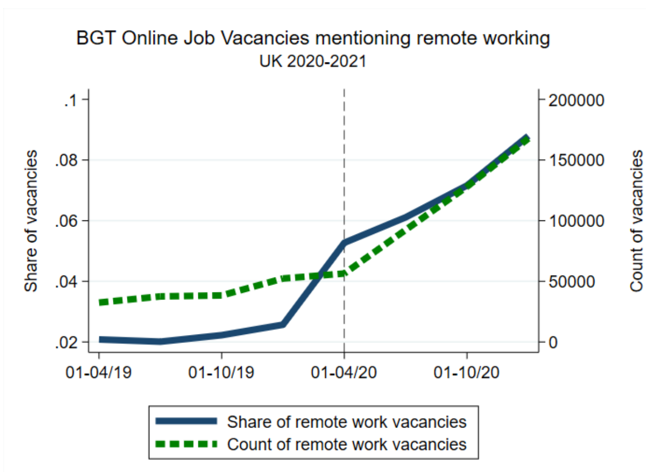
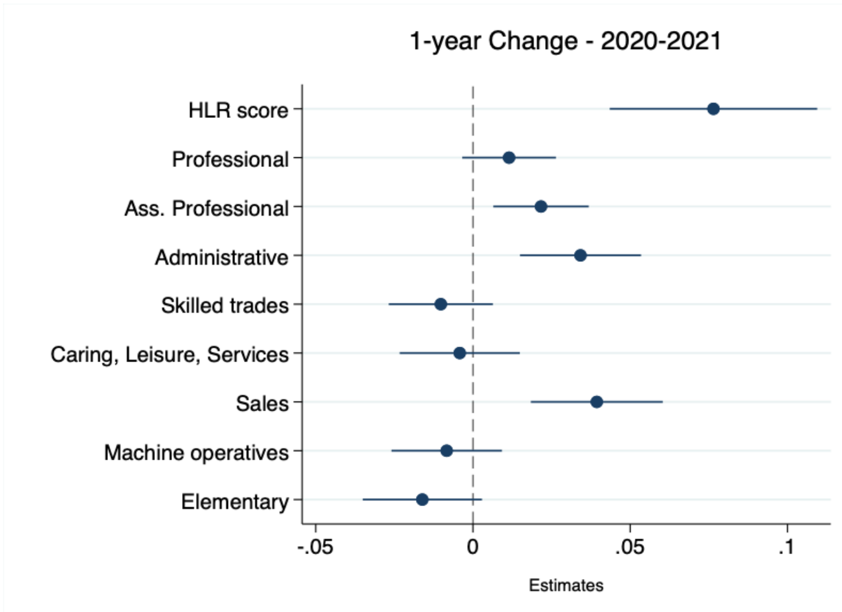
Figure 1: Aggregate Increase in Remote Working during the Pandemic

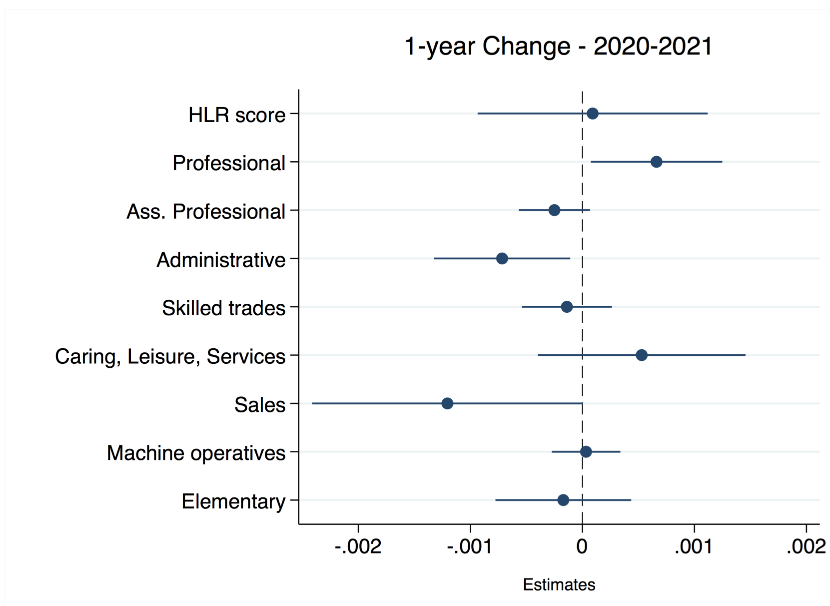


Notes: This figures shows the monthly trends in BGT remote work vacancies in terms the share in total vacancies (left axis) and also in absolute numbers (right axis).

Figure 2: Occupation-level Changes



(a) Remote Work Shares

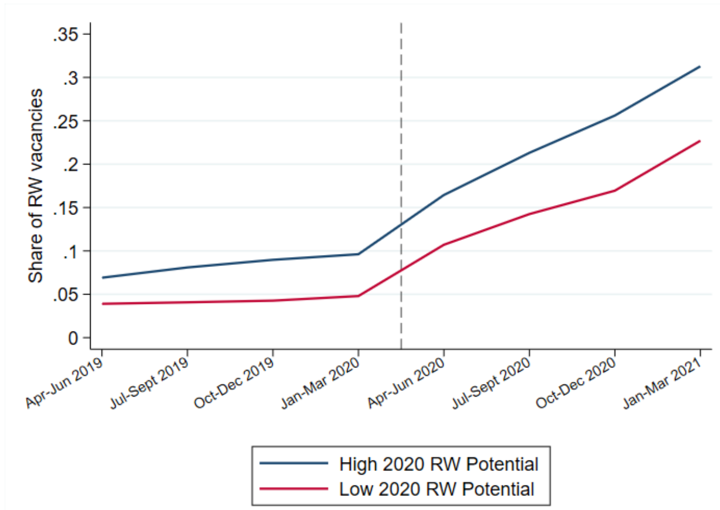


(b) Overall Vacancy Shares

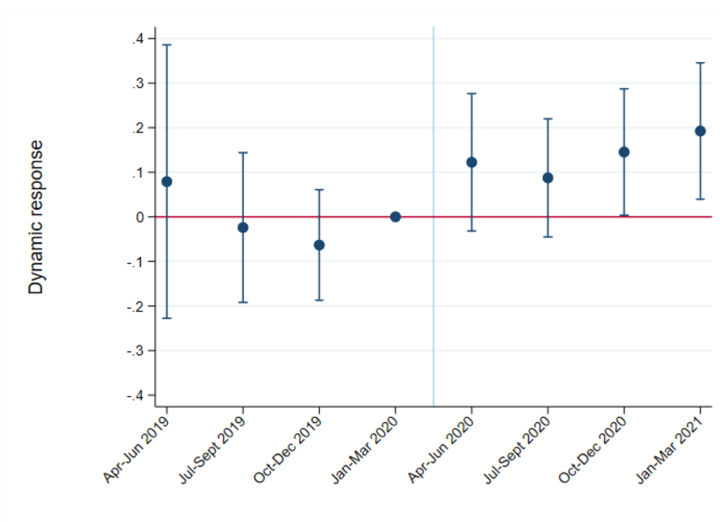
Notes: (a) shows estimates for a regression of within-occupation remote work shares on the HLR feasability score and SOC1 dummies. (b) shows estimates from a similar model but using total occupational vacancy shares as the dependent variables. Both models use 4-digit occupation-year data over the financial years 2020 and 2021, with N= 364 observations. Robust standard errors with 95% confidence intervals plotted.

Figure 3: The evolution of the share of remote-work vacancies in low- vs. high-remote work potential firms

(a) Share of vacancies mentioning remote working by 2020 remote work potential

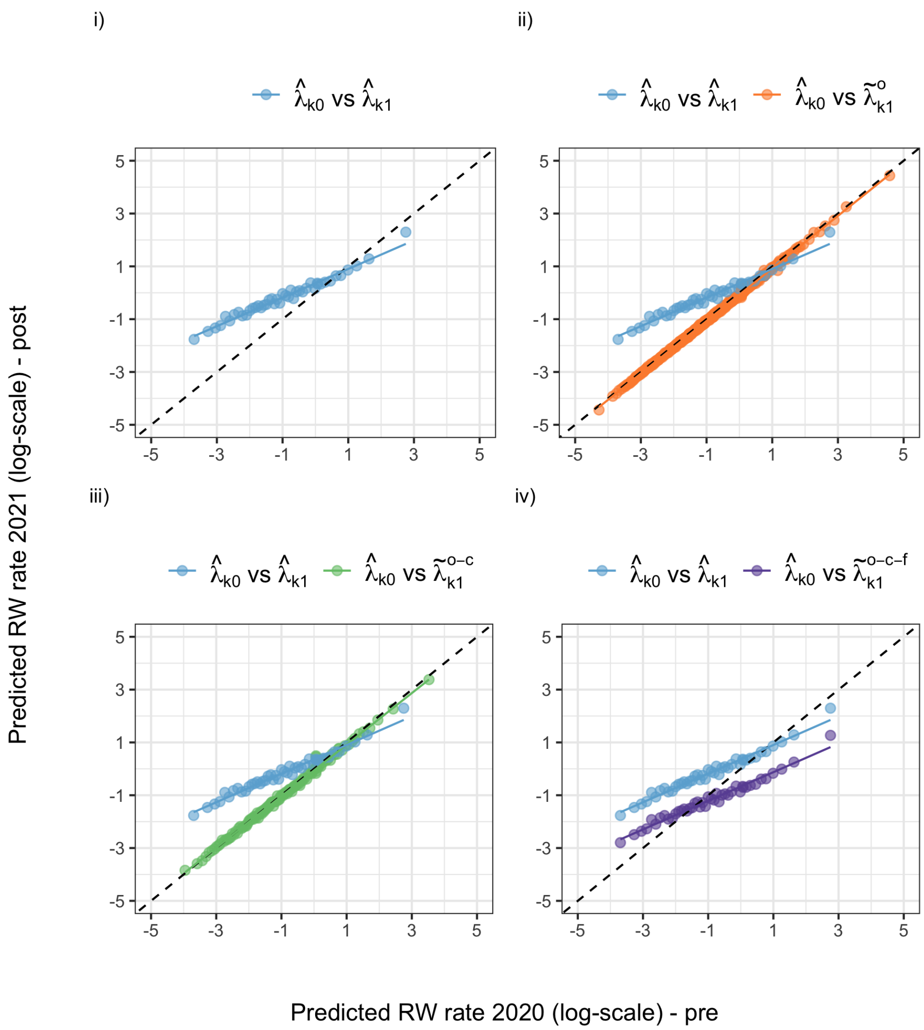


(b) Event study: Difference in the share of remote work vacancies between high and low remote work potential firms.



Notes: (a) compares the evolution of the share of remote-work vacancies for high- and low-RW potential firms. The sample includes firms present in BGT from April 2019 to March 2021 with at least one RW vacancy posted over this period of time. Low (High) RW potential employers are those in the bottom (top) 50% of the RW potential distribution, calculated using employers' pre-covid occupational composition and occupation-HLR scores. The vertical dash line indicates the start of the first UK lockdown. (b) presents the estimates of the coefficients on the interaction between a low-potential dummy and quarter dummies (2020Q1 being the reference) in an event-study Poisson regression at the level of firm and quarter where the count of remote-work vacancies is the outcome conditioning on the total number of vacancies, and with quarter dummies as controls. We report 95% confidence intervals. Standard errors clustered at the firm-level.

Figure 4: Decomposing firm from occupation effects



Notes: these figures plot binscatters of firm-level predicted RW rates in the pre-covid (x-axis) and in the post-covid (y-axis) years.

i) $\hat{\lambda}_{k0}$ vs $\hat{\lambda}_{k1}$: The predicted RW rate has increased more in firms with low pre-pandemic RW rate.

ii) $\hat{\lambda}_{k0}$ vs $\tilde{\lambda}_{k1}^{o}$: If only the occupation RW propensity were to change between the pre-covid and post-covid years, we would virtually see no change in the predicted RW rate.

iii) $\hat{\lambda}_{k0}$ vs $\tilde{\lambda}_{k1}^{o\text{-}c}$: If only the occupation RW propensity and vacancy structure were to change between the pre-covid and post-covid years, we would virtually see no change in the predicted RW rate.

iv) $\hat{\lambda}_{k0}$ vs $\tilde{\lambda}_{k1}^{o\text{-}c\text{-}f}$: Firm propensity is the main driver of the change in RW rate.

Table 1: Impact of the pandemic on RW offer by 2020 RW Potential

	(1) Above/Below median	(2) 5 quintiles
Pandemic × RW Potential (Bottom 50%)	0.154*	
	(0.084)	
Pandemic × RW Potential (q1)		0.088
		(0.109)
Pandemic × RW Potential (q2)		0.326***
		(0.095)
Pandemic × RW Potential (q3)		-0.024
		(0.111)
Pandemic × RW Potential (q4)		0.023
		(0.098)
Observations	97763	97763
Employers	16723	16723
Pre-Pandemic Mean	1.16	1.16
Employer FE	✓	✓
Quarter FE	✓	✓

Source: BGT Apr- 2019-March 2021.

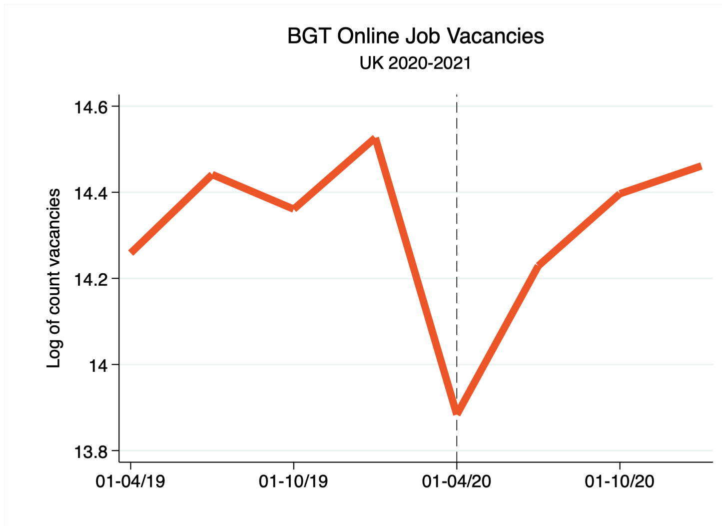
Notes: This table compares the main DiD effects displayed in Column 1 with the effects on firms in each quintile of the 2020 RW potential relative to firms in the top quintile (Column 2). The sample includes firms present in BGT between 2020-2021 and with at least 1 RW vacancy between fiscal years 2020-2021. In Column 1, Low (High) RW potential employers are those in the bottom (top) 50% of the RW potential distribution, calculated using employers' pre-covid occupational composition and occupation-HLR scores. All regressions also include firm and quarter fixed effects. Heteroskedasticity-robust standard errors clustered at firm level in parenthesis. The pre-pandemic mean refers to the sample mean of the outcome variable before the start of the pandemic.

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

Appendix

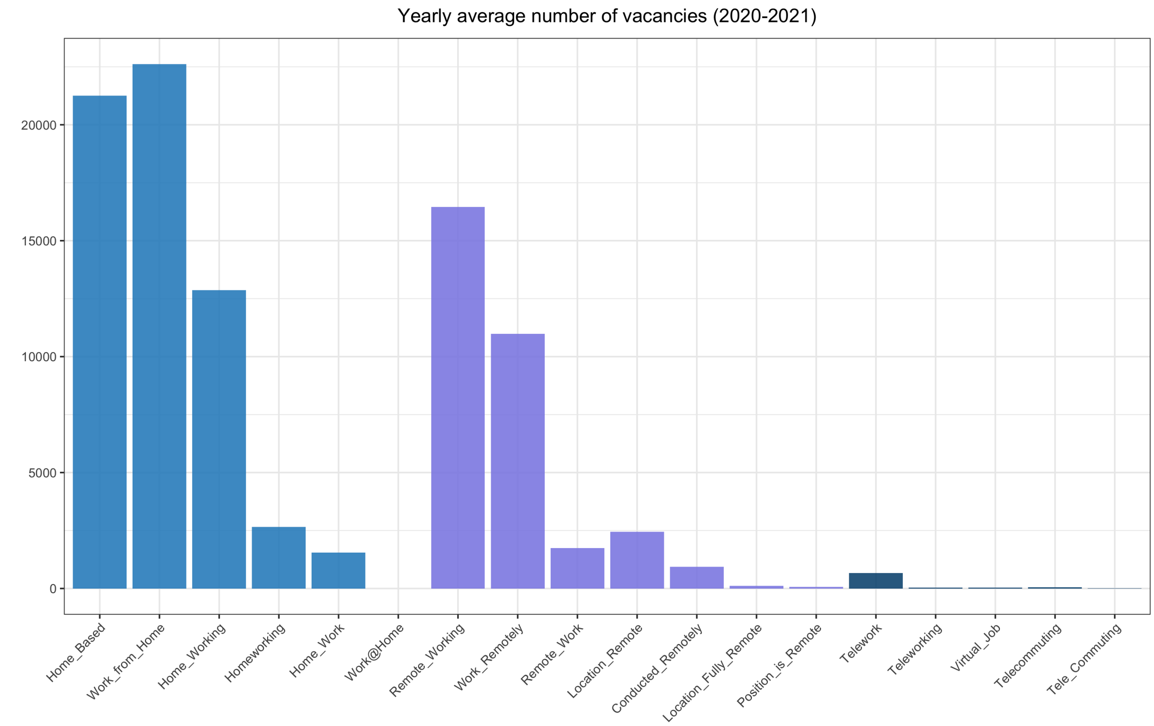
A BGT data

Figure A1: Evolution of labour demand - 2019/20 to 2020/2021



Notes: This figure describes the evolution of labour demand before and after the start of the pandemic using BGT online vacancy data.

Figure A2: Text-based Indicators of Remote Work Vacancies.

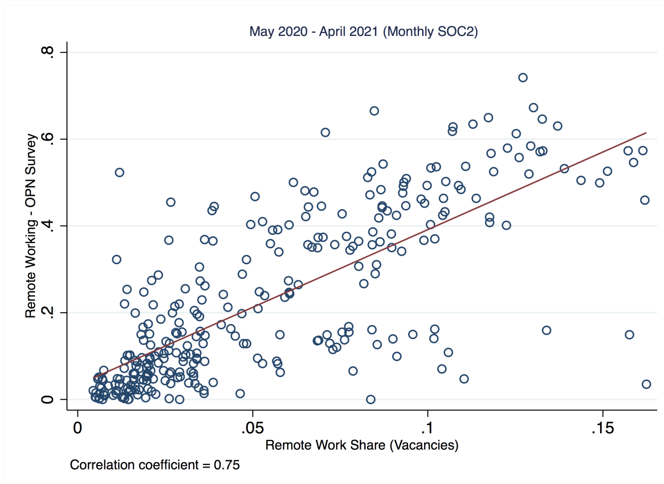


Notes: The figure shows the average number of vacancies mentioning each of the 18 expressions we use over the financial years 2020 (Apr2019-Mar2020) and 2021 (Apr2020-Mar2021). We use the sample of vacancies with both occupation codes and employer names (6.2 million vacancies, which correspond to 46% of all vacancies posted over our period of interest). If a single vacancy would mention two or more terms, it would be counted multiple times. Bars in blue show counts related to home based work. Bars in purple show counts related to remote working. Bars in dark blue show counts related to teleworking.

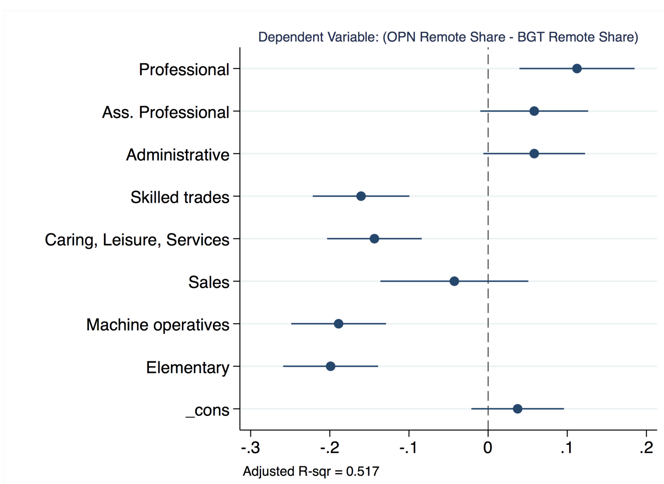
B Occupation-level analysis

Figure B1: Comparing OPN Survey-based and BGT Vacancy-based Remote Work Measures

(a) SOC2-level analysis



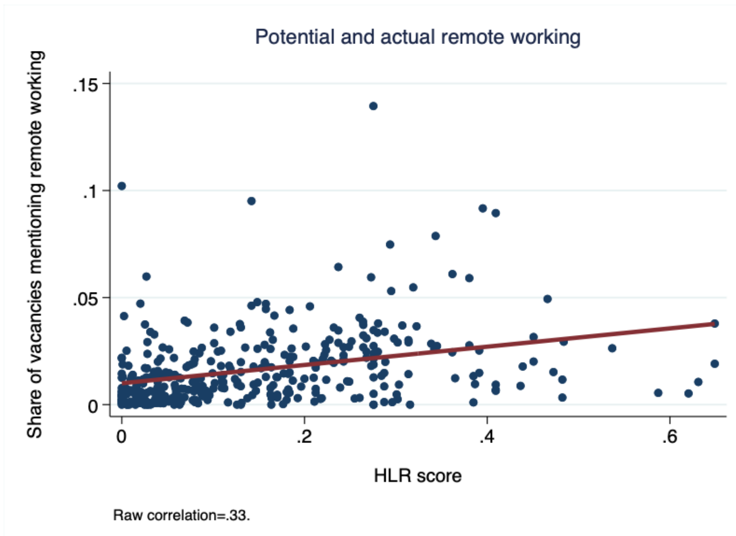
(b) SOC1-level analysis



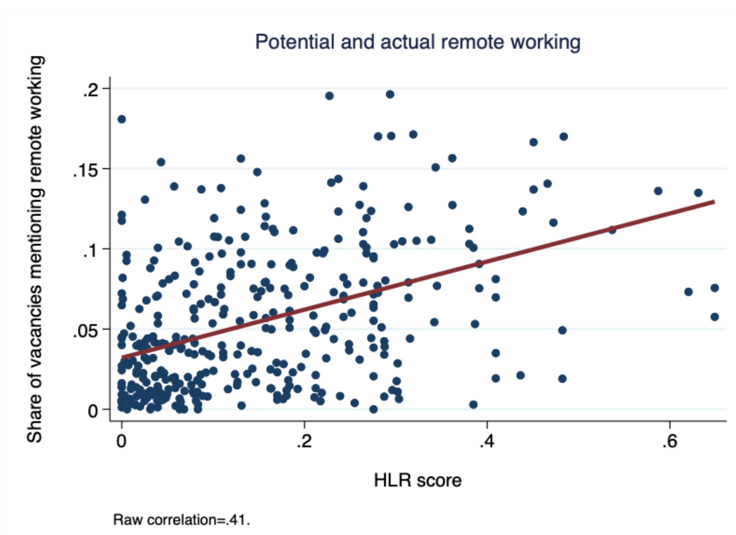
Notes: (a) Shows the correlation between the OPN survey-based and BGT vacancy-based remote working measures. The units are shares in the 0-1 interval. The data is at the SOC2-month level between May 2020 and April 2021 with N=300 observations. The OPN measure is specifically the share of workers who worked at home exclusively (ie: no partial working). (b) shows the coefficient estimates for a regression of the difference between the survey-based OPN and vacancy-based BGT remote work measures on SOC1 dummies. Month-SOC2 data with N=300 observations and robust standard errors. Managerial occupations are the baseline group in the constant. Time effects are residualised out first and approximately 0.17 should added to this constant to retrieve sample means.

Figure B2: BGT Vacancy-based Remote Work versus HLR(2020) Remote Work Feasibility

(a) 2019-2020

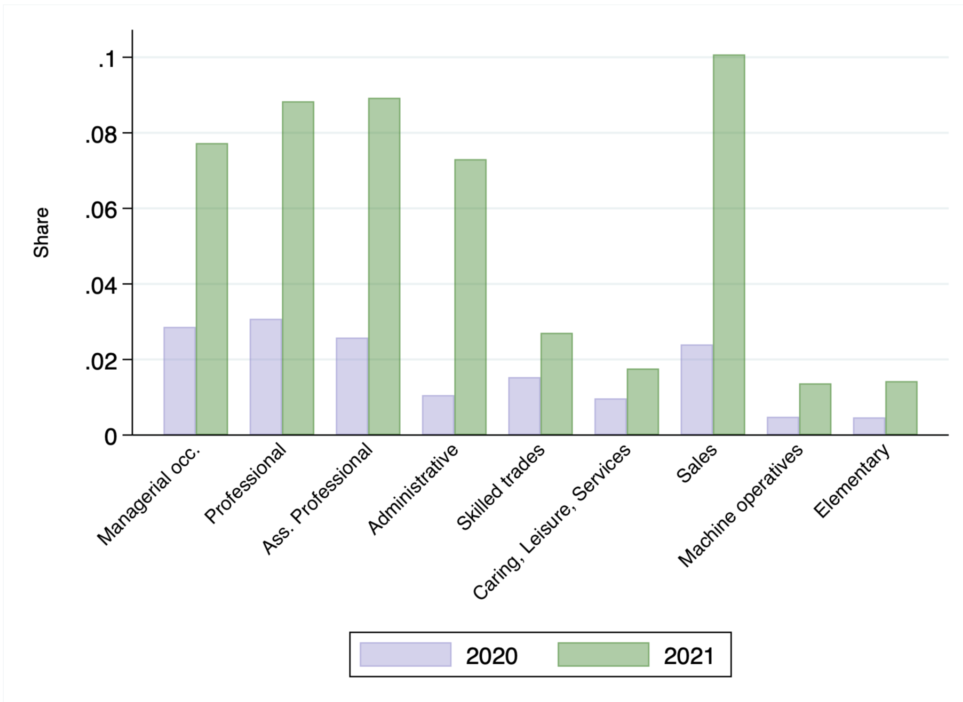


(b) 2020-2021



Notes: these figures shows the cross-sectional, occupation-level relationship between the share of vacancies mentioning remote work opportunities and the HLR score, measuring the average share of hours worked at home by occupation in the ATUS 2011-2018. In panel (a) the share of vacancies mentioning remote work opportunities refers to the pre-pandemic period, that is the financial year 2019/2020, while panel (b) refers to the financial year 2020/2021.

Figure B3: Occupational Breakdown of Remote Work Vacancies.



Notes: The figure shows the share of remote vacancies in total BGT vacancies per 1-digit SOC group. Remote vacancies are defined according to our text-based measure (see section 3.2). The years are defined according to financial year (2020: Apr 2019-Mar 2020; 2021: Apr 2020-Mar 2021).

C Sample definitions

C.1 Difference-in-differences sample

The unit of analysis in our difference-in-differences (DiD) analysis is firm-quarter. As part of this sample, we include firms that hire in both fiscal year 2020 (Apr 2019 - Mar 2020) and in fiscal year 2021 (Apr 2020 - Mar 2021). Among these firms, we further condition on those firms that offer some remote working positions during the two fiscal years. Finally, while the firms are required to hire in both fiscal years we do not impose that they hire in each quarter. Appendix Table C1 describes the resulting sample. The relevant comparison at this point is between columns(1) and (3), representing our difference-in-differences sample and the excluded firms respectively. This shows that the excluded firms are much smaller in size (7 vacancies on average versus 138 for the DiD sample) and feature a much lower share of remote work positions (0.01 versus 0.08).[A.1]

Overall, the employers in the DiD sample post 2.3 million vacancies in fiscal year 2020, which account for 70% of the number vacancies used over this period (ie. the sum of columns (1) and (3) in Appendix Table C1). As discussed, the vacancy information from the excluded employers is still pooled into our aggregate and occupation-level datasets.

C.2 Decomposition analysis sample

The objective of our decomposition exercise is to distinguish occupation-driven changes in the offering of remote work from firm-specific factors. The unit of observation for this analysis is therefore the firm-SOC3 occupation level.[A.2] In turn, this analysis requires some additional conditioning to make the decomposition econometrically feasible.

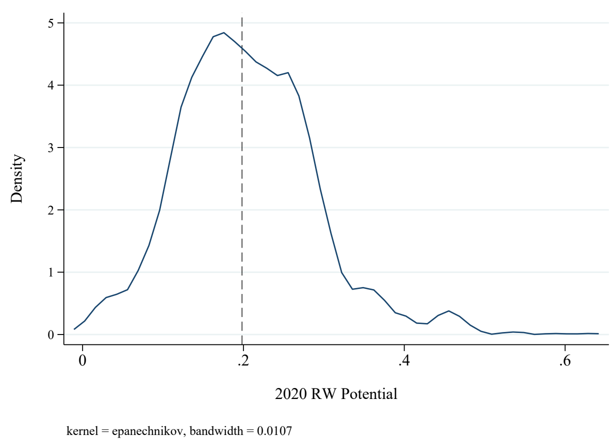
Specifically, in order to estimate the remote work propensity of firm k in year t, α_{kt}, we use remote work variation across occupations hired by firm k in year t. In order to estimate the remote work propensity of occupation j in year t, γ_{jt}, we use remote work variation across firms that hire occupation j in year t. We therefore select occupations that offer some remote working in each year (90 SOC3 occupations). Among firms belonging to the DiD sample, we select all those employers

[A.1]Note that these remote vacancies amongst excluded firms are due to 'unbalanced' firms, that is, the firms that do not have both pre and post-pandemic observations.

[A.2]We consider a 3-digit level occupational code to ensure the estimation of all occupation-year fixed effects for the ninety 3-digit level occupations available. We do this not to alter firms' true occupational compositions when computing firm-level remote work rates.

who offer at least some remote work opportunities in each fiscal year of the data. As shown in Column 2 of Appendix Table C1 the number of firms is reduced from 16,723 to 4,872 such that the decomposition sample features significantly larger firms on average. We discuss the relevance of this conditioning for our results in Section 5.

Figure C1: Remote-work potential measure



Notes: The graph shows the distribution of employers' pre-covid (Apr 2019-Feb 2020) remote-work potential, constructed as described in equation 2. This corresponds to the weighted average of the number of hours that a firm's employees could work from home in the pre-covid year, obtained by averaging its 4-digit occupations HLR scores, weighted by the share of vacancies in each of these occupations. The sample includes firms present in BGT from April 2019 to March 2021 with at least one RW vacancy posted over this period of time.

Table C1: Summary statistics - All BGT employers - 2020

	DiD		Decomposition		Excluded	
Avg N Vacancies	137.89	(2514.0)	339.27	(4640.1)	7.29	(49.33)
Avg N RW Vacancies	3.36	(27.69)	10.58	(50.42)	0.05	(2.784)
Avg N Vacancies for high-remotable occ	94.30	(1940.2)	237.76	(3584.6)	4.29	(29.78)
Avg Share high-remotable	0.75	(0.265)	0.78	(0.197)	0.61	(0.434)
Avg Share RW Vacancies	0.08	(0.201)	0.18	(0.275)	0.01	(0.103)
Share Manufacturing	0.03	(0.174)	0.03	(0.165)	0.04	(0.189)
Share Distrib. & Hospit.	0.05	(0.212)	0.04	(0.187)	0.10	(0.294)
Share Profes. Act.	0.08	(0.264)	0.07	(0.260)	0.04	(0.193)
Share Public., Edu., Health	0.14	(0.342)	0.15	(0.353)	0.14	(0.351)
N employers	16723		4872		136526	
N employer-quarter	48602		16786		214023	
N vacancies	2305889		1652926		995533	

Source: BGT fiscal year 2020 (Apr 2019 - Mar 2020).

Notes: The table compares the characteristics of 3 samples: the one used in the difference-in-differences analysis (column 1), the one used in the decomposition analysis (column 2), the one with employers excluded from the two analyses (column 3).

Table C2: Summary statistics by 2020 RW Potential

	High RW Potential		Low RW Potential	
Avg N Vacancies	82.62	(300.0)	193.16	(3541.9)
Avg N RW Vacancies	3.67	(24.78)	3.05	(30.31)
Avg N Vacancies for high-remotable occ	69.16	(247.1)	119.45	(2732.6)
Avg Share high-remotable	0.90	(0.117)	0.61	(0.290)
Avg Share RW Vacancies	0.10	(0.229)	0.05	(0.165)
Avg HLR score	0.27	(0.0618)	0.14	(0.0434)
Share Manufacturing	0.02	(0.146)	0.04	(0.197)
Share Distrib. & Hospit.	0.04	(0.184)	0.06	(0.236)
Share Profes. Act.	0.11	(0.307)	0.05	(0.209)
Share Public., Edu., Health	0.10	(0.298)	0.17	(0.377)
N employers	8362		8361	
N employer-quarter	23800		24802	
N vacancies	690888		1615001	

Source: BGT fiscal year 2020 (Apr 2019 - Mar 2020).

Notes: This table reports summary statistics by pre-covid RW potential. The sample includes firms present in BGT between fiscal years 2020 and 2021, and with at least 1 RW vacancy over this period of time. Low (High) RW potential employers are those in the bottom (top) 50% of the RW potential distribution, calculated using employers' pre-covid occupational composition and occupation-HLR scores. High-remotable vacancies include vacancies for occupations with an HLR score greater or equal than the median occupational score.

Table C3: Impact of the pandemic by 2020 RW Potential - DiD vs. decomposition sample

	(1) DiD sample	(2) Decomposition sample	(3) No decomposition sample
Pandemic × RW Potential (Bottom 50%)	0.154*	0.169	-0.021
	(0.084)	(0.108)	(0.081)
Observations	97763	33316	64447
Employers	16723	4872	11851
Pre-Pandemic Mean	1.16	3.07	0.15

Source: BGT Apr- 2019-March 2021.

Notes: This table compares the estimates of regression 3 on the entire DiD sample, the decomposition sample, and firms excluded from the decomposition analysis. The outcome is the number of vacancies mentioning RW opportunities. The DiD sample includes firms present in BGT between 2020 and 2021 and with at least 1 RW vacancy between 2020-2021. The decomposition sample includes firms present in BGT between 2020 and 2021, and with at least 1 RW vacancy in both 2020 and 2021. Low (High) RW Potential employers have a 2020 RW Potential below (above) the median RW potential across employers, based on their 2020 occupational composition and occupation-HLR scores. All regressions also include firm and quarter fixed effects. Heteroskedasticity-robust standard errors clustered at firm level in parenthesis. The pre-pandemic mean refers to the sample mean of the outcome variable before the start of the pandemic.

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