# Remote working and the new geography of local service spending.*

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**Abstract**

Remote working, at least some of the time, has rapidly become the new norm in many sectors. Remote working changes where workers spend much of their time, and because of this, it also changes the geographical location of demand, particularly in sectors which supply local personal services (LPS). We quantify this change for England and Wales. To do this, we use a bespoke, nationally representative survey of nearly 35,000 working age adults, which predicts long-term changes in remote working and in LPS spending while at work. On average, we find that a neighbourhood to which people commute 20% less often experiences a decline in LPS spending of 7%. There is a clear geographic pattern to these spending changes: large decreases in LPS demand are concentrated in a small number of city-centre neighbourhoods, while increases in LPS demand are more uniformly distributed. Further analysis of neighbourhoods geographical and socio-demographic characteristics shows the least affluent neighbourhoods see least benefit from remote work.

**Keywords:** Remote working, Work-from-home, Local labour markets, Local personal services, Retail industry, Hospitality industry.
**JEL Classifications:** R12, J01, H12.

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# 1 Introduction

The sudden rise of remote working has altered where workers spend their time and this has been widely recognized. What is less widely acknowledged is the effect this change has had on *where* they consume their working time *local personal services* (LPS), such as coffee, lunches and haircuts[1]. When workers work remotely, morning coffees previously purchased on their commute to the office now may be bought in the neighbourhood where they live. Likewise, workers may switch their gym membership from one near their office to one nearer home. They also may change where they meet friends and co-workers for dinner or drinks, and perhaps use a different supermarket. This paper studies the shift in the geography of work and the consequences of these changes for spending and employment in the LPS industry.

We use information from a new, bespoke, nationally representative, survey of nearly 35,000 UK workers. This survey provides three important pieces of information: how many days a week workers plan to work remotely after 2022; how much time workers spent working remotely before the 2020 pandemic; and how much they spent on retail and hospitality on their workdays at or near their workplace, which we know as their work and home postcodes are reported in the survey, also before the 2020 pandemic. We combine this information with the methodology proposed by De Fraja et al. (2021a), and census data on the distribution of where workers work and where they live, to estimate the post-pandemic change in retail and hospitality spending due to remote working across 7,201 neighbourhoods in England and Wales.

On the back of this, we document three important findings. First, a persistent increase in remote working, and a corresponding shift in the geography of work, large enough to have substantial effects on the geographic location of spending patterns. Remote working will be 20 percentage points greater than pre-pandemic levels. This augurs a substantial shift of workers away from office-dense city centres to residential suburbs.

[1] Our use of this term follows Autor and Reynolds (2020) who give as examples "food service, cleaning, security, entertainment, recreation, health aides, transportation, maintenance, construction, and repair". In this paper we focus on the subset of these which are purchased and consumed dependent on where a person *is*, rather than simply on where they live. For example, our focus includes food service but not construction or repair.

Second, the consequences of remote working for LPS workers will be dramatic. These workers account for approximately 20% of the total labour force in England and Wales. While employment losses are concentrated in city centres, increases in the demand for workers are spread across many residential suburbs and smaller commuter towns. We show a stark asymmetry across gains and losses. For example, one central London neighbourhood, with a population of 9,721, is expected to lose 8,000 LPS jobs. This loss is equilvelent to the total increase in LPS jobs across the 161 largest-gaining neighbourhoods, with a combined population of over 1.55 million.

Third, we identify the role played by the different patterns of spending by remote workers on LPS employment and their different contribution to LPS spending in the neighbourhood. To do so we identify and compute another important metric, the *LPS spending elasticity*. This elasticity reflects, for a given neighbourhood, the percentage change in LPS spending following a percent change in work done in the neighbourhood because of remote working. Our average estimate of this number is 0.35, suggesting that a 20% decrease in the number of workers commuting into a city centre is expected to decrease LPS spending by 7%. This elasticity varies across the country, with most neighbourhoods having values between 0 and one half. But the elasticity is notably higher, approaching one, in neighbourhoods, such as financial districts, where workers' spending is a very large portion of overall spending on personal local services. Our estimates of this elasticity will aid policymakers by quantifying the effects that place-based policies to reallocate workers within urban centres might have on spending in each localised neighbourhood.

As a final exercise, we identify the variables associated with the intensity of the shock to LPS spending in the neighbourhood. Understanding where these shocks are most severe is another essential ingredient to policy making. We consider two groups of variables: those that describe the geographical and economic characteristics of the neighbourhood, such as population density, the extent of retail floor space and internet coverage; and those that reflect the socio-economic status of the neighbourhood's residents such as the deprivation index, the average age, and the average number of people living at the same address. The general message for this analysis is that more prosperous areas fare better than less affluent ones for a similar-sized shock to LPS spending.

Our analysis complements work done on the increase in remote working in the US (Barrero et al., 2021) and updates earlier estimates for the UK (Casey, 2021). We also build on previous work on how remote working will affect where work is done in the UK (De Fraja et al., 2021a), and the US (Ramani and Bloom, 2021), (Althoff et al., 2021), and (Brueckner et al., 2021). We make several contributions to this literature. A key feature, relative to US studies, is that we are able to observe the pre-pandemic distribution of workers at a very granular level by place of work and place of residence. This allows us to calculate neighbourhood specific changes in spending, as opposed to aggregate spending shifts for the entire urban centre. Second, unlike the previous work of De Fraja et al. (2021a), our access to novel survey data allows us to calculate the percentage change in remote working relative to pre-pandemic levels and the accompanying percentage change in spending.

The remainder of the paper is structured as follows. Section 2 outlines our conceptual framework. Section 3 presents our results, and Section section 4 briefly concludes. Details of our data and how we handle it are in appendix A.

## 2 The conceptual framework

To fix ideas we consider an economy with two types of workers, those who work in industries supplying local personal services and all other workers. We refer to the former as LPS workers. In practice, an important difference between these two types of workers is that non-LPS workers have jobs for which some portion of the work, in many cases all the work, can be done remotely, while the LPS jobs must be done entirely onsite. We think of an economy as partitioned geographically into non-overlapping neighbourhoods, indexed by $z$. The sets of individuals whose place of work and residence are respectively in neighbourhood $z$ in year $t = \{2019, 2022\}$ are denoted as $I_z^{W,t}$ and $I_z^{R,t}$. Each worker $i$ is characterized by a pair $\left(\rho_i^{2019}, \rho_i^{2022}\right) \in [0,1]^2$, where $\rho_i^t$, the remote workability index, measures the percentage of worker $i$'s job done remotely in the two years. In the absence of more information about where workers are when they work remotely, we assume that work done remotely is done in (the neighbourhood of) the worker's main residence. With this assumption, we define the amount of work performed in neighbourhood $z$ and year $t$ as

$$E_z^t = \sum_{i \in I_z^{W,t}} \left(1 - \rho_i^t\right) + \sum_{i \in I_z^{R,t}} \rho_i^t, \qquad t = 2019, 2022. \tag{1}$$

where $I_z^{W,t}$ is the set of workers who work in neighbourhood $z$ and $I_z^{R,t}$ is the set of workers who live in neighbourhood $z$. To gain an intuitive understanding of (1) consider its values at the extremes of remote working. If all workers work in the office, $\rho_i^t = 0$ for every $i$, then $E_z^t$ equals the number of workers whose place of work is in neighbourhood $z$. If all workers work remotely, $\rho_i^t = 1$, then $E_z^t$ will be equal to the number of workers who live in neighbourhood $z$.

We define the *zoomshock* as the total change in the quantity of work done in a neighbourhood $z$ between 2019 and 2022 (following De Fraja et al. 2021a) due to the change in remote working. Using the notation above, this can be written as

$$\Delta E_z = E_z^{2022} - E_z^{2019}. \tag{2}$$

If remote working increases between 2019 and 2022, then one expects $\Delta E_z$ to be positive for residential neighbourhoods, where many people live relative to the number who work there, and negative for city centres where many people work. The zoomshock affects the demand for LPS goods in neighbourhood $z$ to the extent that the LPS goods are consumed at or near the place of work. Formally, let $s_i \geq 0$ be the amount spent by individual $i$ on LPS goods and services while at work. We can define:

$$S_z^t = \sum_{i \in z^{W,t}} s_i \left(1 - \rho_i^t\right) + \sum_{i \in z^{R,t}} s_i \rho_i^t, \qquad t = 2019, 2022, \tag{3}$$

as the total expenditure in year $t$, $t = \{2019, 2022\}$, on LPS goods by individuals who work in neighbourhood $z$. This is the sum of the expenditure of those *working* in neighbourhood $z$ who do not work remotely and the expenditure by those *residing* in neighbourhood $z$ who instead do work remotely. The change in LPS expenditure between 2019 and 2022 due to changes in remote working is then:

$$\Delta S_z = S_z^{2022} - S_z^{2019}. \tag{4}$$

There are three assumptions worth highlighting in order to correctly interpret (4) as neighbourhood $z$ LPS spending change. First, our calculation of assumes that all spending moves from the neighbourhood where people work to those where people live. In practice, however, while the decrease in spending is likely to be greater when workers leave city centres, than the corresponding increase in residential neighbourhoods, if relatively few LPS services are available in these neighbourhoods. For this reason, we interpret $\Delta S_z^t$ as the geographic shift in *desired* retail and hospitality spending by workers. Second, we assume that desired spending on retail and hospitality does not change when workers work remotely as opposed to working in an office. It is plausible that when workers work from home LPS demand will fall, given access to a stocked pantry and a familiar kitchen. On the other hand, it could also be that desired spending increases, as coffee shops and restaurants may provide an appealing respite from the social isolation of remote working. For this reason, we make the intermediate assumption that *desired* spending is independent of where work takes place. Thus, actual local spending will be affected only by constraints on supply. Third, in practice some people may enjoy post work drinks in a bar with colleagues once a week whether they work five or two days in the office, and conversely others may swap the gym close to work with one near their home, even if they still work three days in the office. We make the assumption that spending during the working day is spread evenly throughout the week.

We compute two additional metrics based on the zoomshock and spending shift calculations. The first is the LPS elasticity: the percentage change in LPS spending divided by the percentage change in work done in neighbourhood $z$:

$$\eta_z = \frac{\Delta S_z + \Delta \Omega_z}{\Delta E_z} \Big/ \frac{S_z^{2019} + \Omega_z^{2019}}{E_z^{2019}}. \tag{5}$$

In the above, $\Omega_z^t$ is the expenditure by people who neither work nor live in neighbourhood $z$: tourists, shoppers, and so on. As our calculation is focused on the effect of remote working on LPS spending, we impose that $\Delta\Omega_z = \Omega_z^{2022} - \Omega_z^{2019} = 0$ in our empirical application.

The second measure that we consider is the impact that the change in LPS spending, due to remote working, will have on employment in neighbourhood $z$ if our assumptions hold. We denote this value by $\tau_z$ where:

$$\tau_z = \overbrace{\underbrace{\frac{\Delta S_z + \Delta\Omega_z}{S_z + \Omega_z}}_{\text{\% change in LS employment}} \times \phi \times E_z^{LS}}^{\text{change in the number of employees}}. \tag{6}$$

where $\phi$ is the employment-spending elasticity of LPS employment, that is the percentage change in employment needed to meet a one percent change in spending. Multiplying this by the number of LPS workers in $z$ in 2019, $E_z^{LS}$, we obtain the numerical change in employment. In our empirical application, we make the simplifying assume that $\phi = 1$; an $x$ percent decrease in LPS spending leads to an $x$ percent decrease in LPS employment. In reality $\phi$ will vary. For example, in some neighbourhoods a small decrease in revenue may lead to many firms being unable to cover the fixed costs and closing and thus $\phi > 1$. For this reason, we regard $\phi = 1$ as a conservative simplifying assumption.

# 3 Empirical analysis

## 3.1 Data

We calculate the values for expressions (2), (5), (6) using data from several sources, details of which we provide in appendix A.

A unique source for our analysis is the bespoke *Work from Home Survey*. This survey has collected information from around 2,500 British adults since January 2021.[2] Using these data we construct, for 16 occupations and 4 regions, an index of remote working in 2019 and 2022, $\rho_i^{2019}$ and $\rho_i^{2022}$ in our notation.[3] This survey also provides information on retail and hospitality spending by workers while at work

[2]We include a full description of the survey in appendix A. Survey participants are UK residents aged between 20 and 65, with annual earnings of at least £10,000 in 2019. We use data from March 2021 to March 2022, for a total of 34,551 observations.

[3]We compute the values of $\rho_i^t$ for worker $i$ from the answers he or she gives to questions regarding hours of work and commuting for $t = 2019$ (details in Appendix A.2.2), and for $t = 2022$ from their answers to the following questions: "After COVID, in 2022 and later, how often would you like to have paid workdays at home?" and "After COVID, in 2022 and later, how often is your employer planning for you to work full days at home?" Specifically, we set $\rho_i^{2022}$ to be the answer to the latter if the respondent is an employee, to the former if they are self-employed. Answers were given in days per week or per month.

in 2019. From this we construct our LPS spending $s_i$, for each of our occupations and regions. The distribution of residents by occupation comes from the 2011 population census for England and Wales. We report summary statistics for these constructed variables in Table 1.[4] Finally, we determine the expenditure by individuals who are neither resident nor workers, $\Omega_z^{2019}$ which is needed to determine the total expenditure on LPS goods, by inferring it from the total output of the LPS workers in the neighbourhood. We obtain this in turn by multiplying the number of LPS workers by their average productivity, which we assume to be the same for all the neighbourhoods in each of the ten broad regions in England and Wales.

The available data require us to make several further assumptions. First, we posit that the number of people residing and remote working in each neighbourhood is the same in 2019 and in 2022. While there is anecdotal evidence that the possibility of remote working has led some people to relocate, there is no evidence of significant household migration in the UK. [5] Secondly, we have assumed that the overall expenditure on LPS goods by individuals who are neither residents nor workers has remained the same, that is $\Omega_z^{2019} = \Omega_z^{2022}$. The validity of this assumption is hard to test without data on who spends what where, but non-systematic data such as restaurant occupancy rates suggests it may be reasonable.[6] Perhaps, as discussed above, more important is the assumption that each individual's desired personal service expenditure near their workplace, is the same when they RW. As above, we regard assuming it is unchanged as a reasonable approximation in the absence of additional information.

Neighbourhoods are defined as Middle Super Output Areas (MSOAs), geographically meaningful census tracts averaging 8,000 residents, designed by the Office for National Statistics (2020).

### 3.2 Results: Distribution of the zoomshock and the LPS elasticity

As anticipated, our measures of the effects of remote working vary widely from neighbourhood to neighbourhood. We illustrate this in Figure 1, which plots $\Delta E_z$, $\eta_z$, and $\tau_z$ for each neighbourhood in the Greater Manchester metropolitan area.

[4] Taneja et al. (2021) report productivity and preference results for earlier waves of the survey.
[5] Relevant data are available here: Number of property transactions.
[6] See, for example, Opentable.

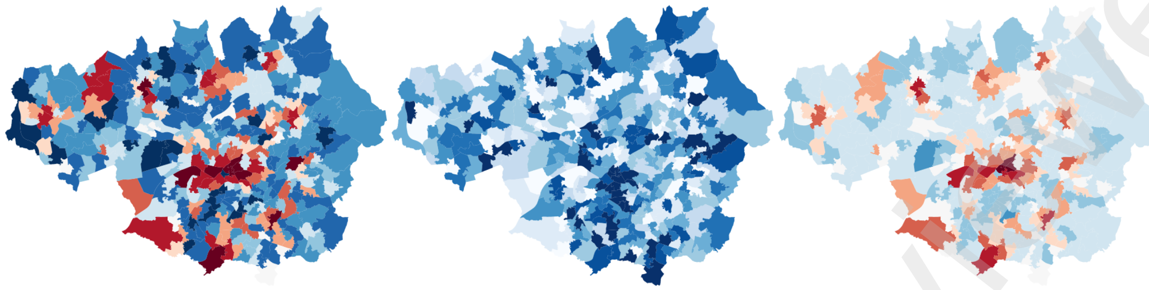
This is the second-largest conurbation in the UK, after Greater London. With a population of 2.85 million, it compares in size with the Tampa, FL, Denver, CO, or Rome, Italy metro areas.[7] Blue (red) areas indicate positive (negative) values of a variable. Deeper colours denote larger absolute values.

All three maps show a pattern of neighbouring areas with sharply different colours, indicating how neighbourhood with very different characteristics border each other, and countering any idea of a smooth change from one part of the metropolitan area to another. Yet, keeping in mind that the resident population of each area is approximately constant, a careful inspection does reveal a pattern: the deep red areas in Panel (a) and (c) are the city centres, Manchester itself and other towns within the region such as Stockport in the south-east, and Oldham to the east. Other larger "red" areas are business parks, where one finds smaller office blocks and other commercial spaces, such as factories, warehouses and distribution depots, but where few people live. Most areas in these two maps are blue; differences in shades of blue are suggestive of specific characteristics of a neighbourhood's residents, as we show in a more systematic way in Section 3.3. Larger areas denote more rural districts, though the balance of well-to-do commuters and agricultural workers will affect the size of the zoomshock, and hence the specific shade of blue an area takes. If the colour pattern in Panels (a) and (c) is roughly similar, the pattern in the middle map, which plots the LPS elasticity $\eta_z$, is sharply different. Neighbouring areas which are filled with similarly red shades in the zoomshock Panel (a) take very different shades of blue in Panel (b), reflecting the different characteristics of the consumers of LPS goods in the areas, for example, shoppers, tourists, or office workers.

The spending elasticity measures the direct effect on LPS spending of a change in of the location of employees during their work time. Therefore, it is independent of the pandemic, it is a measure of employment spillovers from the rest of the economy to the LPS industries. Table 1 reports its average to be 0.363, and that this is higher for neighbourhoods with a negative zoomshock than others (0.383 versus 0.356). Estimates are relatively precise, which makes the difference statistically significant at the 0.1% level. The table also reports summary statistics for variables which will be discussed in Section 3.3.

[7] Maps for other metropolitan areas, London, Birmingham, Cardiff, and Leeds are in the Appendix.

**Figure 1:** Remote working and LPS workers



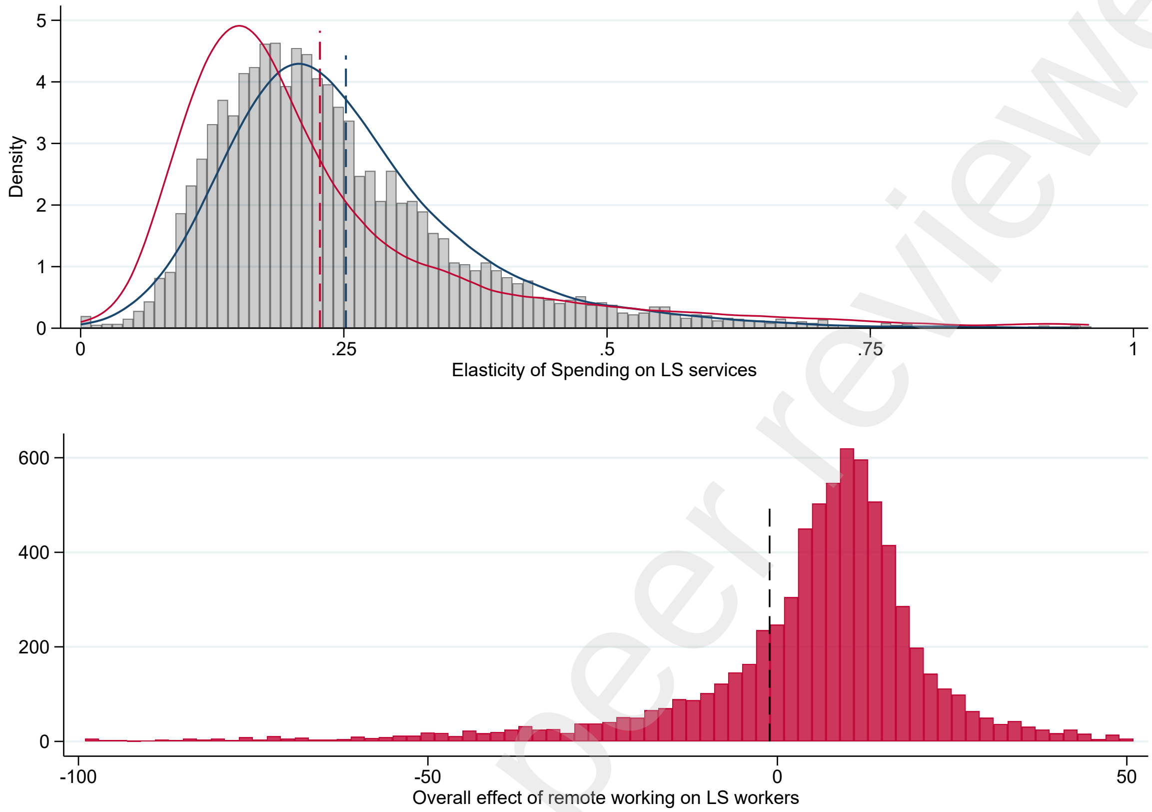
**(a)** Zoomshock ($\Delta E_z$) **(b)** LPS elasticity ($\eta_z$) **(c)** Total effect ($\tau_z$)

*Note:* In the choropleth maps, each MSOA in the Greater Manchester is coloured according to the quantile in which the corresponding variable falls in the ranking of the MSOAs. The leftmost map is the zoomshock, the middle one the LPS elasticity, and the rightmost the overall effect on LPS employment, $\tau_z$ in expression (6). Blue values are positive, red value negative, and a deeper shade indicate a higher value in absolute terms.
*Data source:* ONS Business Structure Database, 2018. Proportion of homework by MSOA based on authors calculations using information from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019, and the Working from Home Survey 2022.

In Figure 2 we report the distribution, across all MSOAs in England and Wales, of the elasticity $\eta_z$, in the upper part of the diagram, and the shock $\Delta E_z$, in the lower part. There are 99 MSOAs where the weighted net outflow of workers exceeds 1000, nine of which over 10,000, among them the City of London, which loses just under 175,000 workers; and 88 MSOAs where the potential increase in the demand for LPS workers is between 500 and 1500. We have excluded these, to avoid stretching the axis too much. In the upper diagram we also exclude 111 MSOAs where the elasticity exceeds 1 and 47 where it is negative: the latter may be due, besides measurement error, to rare cases where working from home leads to changes in LS spending and in the working population that go in opposite directions. This would be the case, for example, if a few high spending commuters leave a neighbourhood as they begin to work remotely, while many low spending residents also start working remotely and so spend their working day in the neighbourhood.

Figure 2 also depicts the kernel density estimates of the distribution of $\eta_z$ disaggregated by whether or not there will be an expected increase, the blue line, or decrease, the red line, in demand. Visual inspection, confirmed by a Kolmogorov-Smirnov test, indicates that areas where the zoomshock is positive have higher elasticity than those where the zoomshock is negative: the vertical dashed lines are the sub-samples means. The relationship between elasticity and zoomshock is

**Figure 2:**
The effect of the zoomshock on LPS employment.

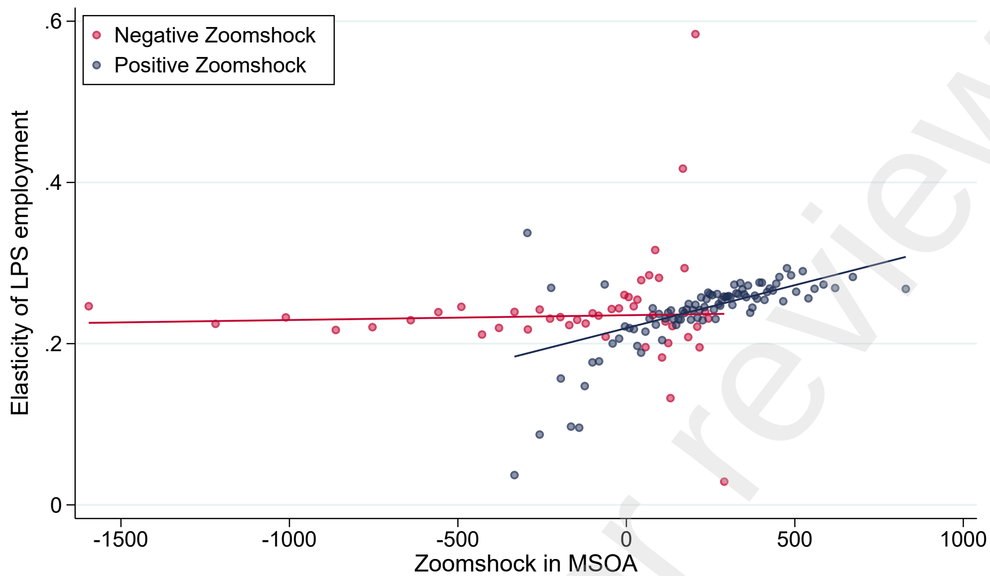



**Note:** The upper figure provides a histogram describing the distribution of elasticities, $\eta_z$, across neighbourhoods (MSOAs) in England and Wales: the width of each bin is 0.01. It also plots kernel density estimates of the distributions for MSOAs with positive (blue curve) and negative zoomshocks (red curve). The lower histogram shows the distribution of the change in LPS employment across neighbourhoods. The width of each bin is 2 workers. In both figures, the vertical dashed lines show the mean of the distribution.

explored further in De Fraja et al. (2021b).

The lower diagram in Figure 2 reports the distribution of the total effect $\tau_z$. Most neighbourhoods experience an increase in demand for LPS, even though the mean of $\tau_z$, indicated by the vertical dashed line, is negative. This reflects the concentration of reductions in demand in comparatively few neighbourhoods. Table 1 shows a mean increase in potential LPS employment in areas with a positive zoomshock of 22 LPS workers. The magnitude is around three times greater in areas with a negative zoomshock, a potential reduction of 67 LPS workers, reflecting the concentration of office work and LPS in city-centres and out-of-town business parks. We note that $\eta_z$ and $\Delta E_z$ are positively correlated in neighbourhoods with

**Figure 3:**
Zoomshock and LPS elasticity.




**Note:** Binscatter plot of the association between the size of the zoomshock, expression (2), and the elasticity of LPS spending expression (5).

positive zoomshocks, but only weakly negatively correlated in those with negative zoomshocks.

Figure 3 illustrates an important further difference between areas with positive and negative zoomshock. While in the areas with a negative zoomshock the association between the zoomshock and the spending elasticity is at best extremely weak, in neighbourhoods with a positive zoomshock, this association is positive though decreasing in strength: a simple quadratic regression including local authority fixed-effects, gives $\eta_z = \underset{(19.29)}{257} + \underset{(4.21)}{.412}\Delta E_z - \underset{(2.83)}{.0001}\Delta E_z^2 + \varepsilon_z$ (as below we have multiplied elasticity by 1,000 to avoid leading zeros and the numbers below the coefficients are $t$-statistics).[8] This implies that in a neighbourhood where many residents work remotely, each remote worker has a relatively larger impact on the employment of LPS workers, relative to low remote working neighbourhoods. A natural explanation for this regularity is that these high zoomshock neighbourhoods are residential areas with relatively many well paid, and hence high spending workers, and not as many of other types of spenders, such as shoppers

[8]The estimates imply the elasticity increases up to around 823 (±183 for the 95% confidence interval): fewer than 1.7% of the MSOAs in England and Wales have a zoomshock larger than this.

and tourists.

### 3.3 Results: determinants of the effects of the zoomshock

One contribution of this paper is to understand how the total effect of remote working on LPS workers, given by $\tau_z$ in (6) varies across neighbourhoods in England and Wales with the demographic and geographical characteristics of neighbourhoods. This will help identify where policy intervention may be most effective.

We aim to identify the association between both the overall effect of the zoomshock, $\tau_z$ in (6), and its separate components, the elasticity $\eta_z$, in (5), and the zoomshock itself, $\Delta E_z$ in (2), with a set of variables chosen to capture three key dimensions along which neighbourhoods vary and which one would expect *a priori* be associated with the type of workers who work or reside in a given neighbourhood, and in particular their propensity to spend and their potential to work remotely, and hence to determine the effect on LPS workers; these three dimensions are: affluence, connectivity, and commercial space.

Formally, we run simple cross-section regressions of the type

$$y_z = \alpha + \boldsymbol{\beta}\mathbf{X}_z + \varepsilon_z, \qquad t = 1, \ldots, 7201. \tag{7}$$

On the LHS of equation (7), we consider separately each of the three terms in equation (6): the zoomshock, $\Delta E_z$; the elasticity, $\eta_z$ ; and the total effect of the zoomshock on the employment in a neighbourhood, $\tau_z$ in (6). The vector of covariates, $\mathbf{X}_z$, includes a neighbourhood deprivation index (IMD), housing quality, housing density (people per house), the average age of a resident, population density (residents per squared kilometer), average broadband speed, percent of households covered by broadband, and a quadratic for retail and office space (in squared kilometers of floor space).

We stratify the empirical analysis according to neighbourhoods with positive zoomshocks, which we refer to as *positive neighbourhoods*, and those with negative zoomshocks, referred to as *negative neighbourhoods*. To fix ideas, one can roughly think of negative neighbourhoods as neighbourhoods where people work, and, pre-pandemic, commuted *to*, and positive neighbourhoods as residential areas where people commuted *from*. The reason for this split is that, as shown by the summary statistics reported in Table 1, positive and negative neighbourhoods have sharply distinct characteristics: Column (7) reports t-tests of the differences of the mean of each variable for positive and negative neighbourhoods, reported in Columns (5) and (6). As a whole, these make it clear that, other than broadband speed, there are systematic differences in all these characteristics between positive and negative neighbourhoods.

**Table 1:** Summary Statistics

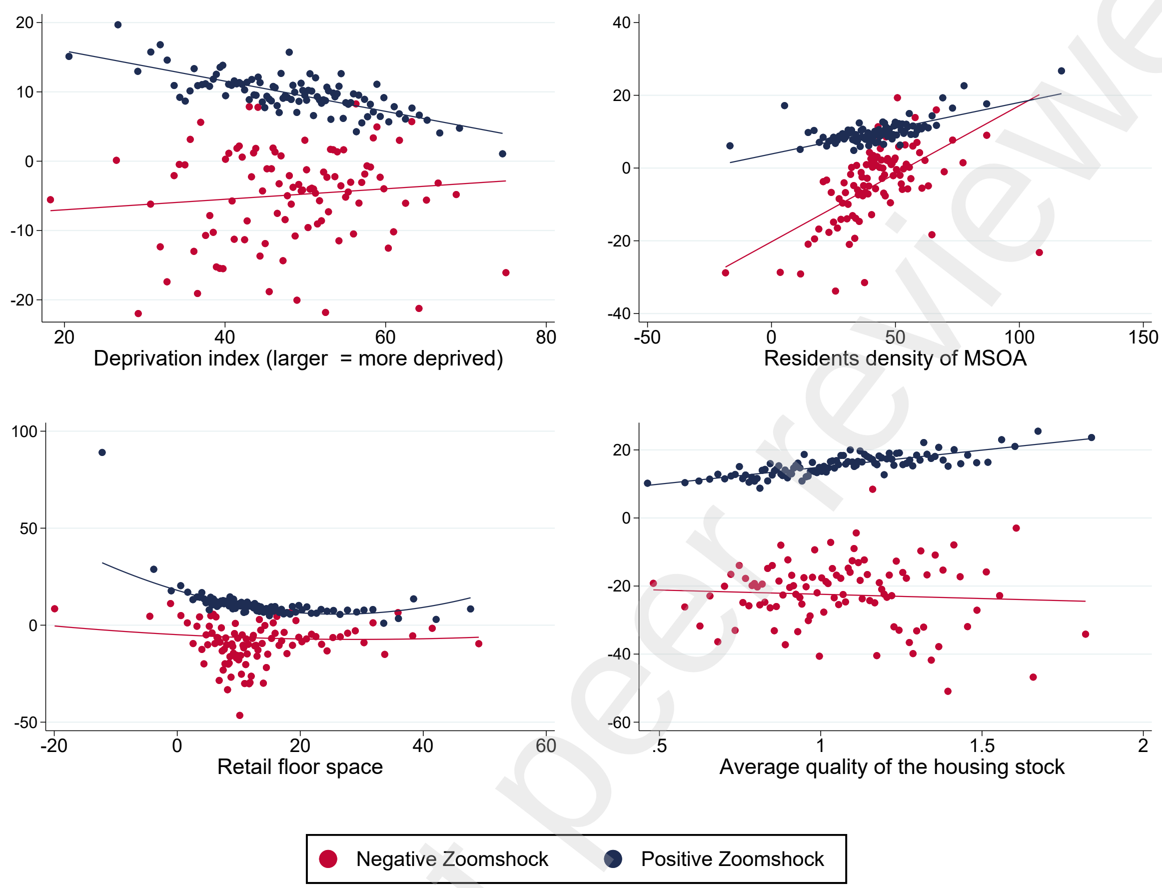
| variable | (1) mean | (2) sd | (3) min | (4) max | (5) Mean neg zs | (6) Mean pos zs | (7) t-test (6)-(5) |
|---|---|---|---|---|---|---|---|
| Zoomshock | 6.787 | 1,944 | -123,670 | 1,842 | -911.3 | 328.8 | 24.73 |
| Elasticity | 0.376 | 0.325 | -2.606 | 18.06 | 0.377 | 0.376 | -0.17 |
| Total effect | -1.555 | 185.5 | -12,373 | 169.6 | -67.42 | 21.55 | 18.26 |
| IMD | 48.32 | 25.07 | 1.109 | 99.98 | 55.07 | 45.95 | -13.72 |
| Housing quality | 1.064 | 0.379 | 0.331 | 2.421 | 0.971 | 1.096 | 12.44 |
| Housing density | 2.294 | 0.283 | 1.031 | 5.181 | 2.259 | 2.307 | 6.31 |
| Average age | 41.34 | 4.943 | 23.93 | 62.40 | 39.80 | 41.87 | 15.88 |
| Density | 42.79 | 40.03 | 0.0878 | 506.2 | 45.36 | 41.89 | -3.23 |
| Broadband speed | 60.98 | 21.37 | 16.92 | 543.7 | 61.28 | 60.88 | -0.70 |
| Broadband coverage | 0.758 | 0.0842 | 0.221 | 0.934 | 0.728 | 0.769 | 18.48 |
| Retail space | 13.85 | 29.10 | 0 | 651 | 34.97 | 6.439 | -40.41 |
| Office space | 11.43 | 77.03 | 0 | 5,346 | 35.89 | 2.847 | -16.25 |

**Note:** Summary statistics for the variables used in the regression reported in table 2. The observations are the 7201 MSOAs in England and Wales; columns (5) and (6) report the mean of those with a negative and a positive zoomshock, 1884 and 5317 in number, respectively, and column (7) the t-test of the difference in their means. They are all significantly different from each other, except the average broadband speed in the MSOA.

A second reason why the analysis is best carried out by splitting the sample is illustrated by Figure 4. This provides binscatter plots of the relationship between the total effect on LPS employment, $\tau_z$, and a selection of independent variables.[9] In each plot we control for neighbourhood characteristics and local authority fixed effects as in regression (7). This implies that the bins on the horizontal axes describe the conditional distribution of the named variable on each axis. This explains why there are negative values for some variables. They show the systematic differences in the relationship between $\tau_z$ and each variable between positive and negative neighbourhoods.

[9] Diagrams for additional variables are in figure B.3 in the online appendix.

**Figure 4:**
Binscatter plots of $\tau$, the LPS employment of the zoomshock.




**Note:** Each diagram is a binscatter plot of the association of the variable on the horizontal axis with the total effect of the zoomshock on LPS workers, expression (6). Each plot reports the relationship conditional on neighbourhood characteristics and local authority fixed effects as in regression (7).

To confirm what Figure 4 suggests visually, we report in Table 2 our regression results for negative neighbourhoods in columns (1)–(3), and positive neighbourhoods in columns (4)–(6). In the regressions with elasticity as the dependent variable, we multiply $\eta_z$ by 1000 to avoid leading zeros.

The first set of covariates measure aspects of how affluent a neighbourhood is. The first of these variables is the index of multiple deprivation (IMD).[10] Intuition, confirmed by De Fraja et al. (2021a), suggests that those living in more deprived areas are least likely to be in jobs where remote working is possible, potentially portend-

[10]This is a weighted average of different aspects of deprivation including income and employment, health, education, crime and housing, and others. The weighting differs slightly between England and Wales, but any impact of these differences will be captured by the local-authority fixed effects.

**Table 2:**
Determinants of the zoomshock

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | MSOAs with negative zoomshocks | | | MSOAs with positive zoomshocks | | |
| Effect on LPS employment | Elasticity | Zoom-shock | Total effect | Elasticity | Zoom-shock | Total effect |
| IMD | -1.248 | 0.430 | 0.0238 | -0.530* | -3.711*** | -0.229*** |
| | (1.225) | (1.300) | (0.0939) | (0.294) | (0.199) | (0.0145) |
| Housing quality | -119.7 | 0.989 | -4.415 | 21.98 | 21.35 | 5.932*** |
| | (75.16) | (106.5) | (8.241) | (21.12) | (16.33) | (1.206) |
| Housing density | -53.99 | -165.9*** | -7.108* | 0.417 | -176.0*** | -13.27*** |
| | (59.12) | (57.01) | (3.875) | (21.05) | (14.81) | (1.143) |
| Mean Age | -2.730 | 20.77*** | 1.575*** | -0.397 | -10.74*** | -0.789*** |
| | (4.469) | (4.915) | (0.358) | (1.529) | (0.979) | (0.0712) |
| Density | 1.274* | 4.517*** | 0.288*** | 0.531** | 1.700*** | 0.114*** |
| | (0.772) | (0.935) | (0.0803) | (0.236) | (0.135) | (0.0112) |
| Broadband Speed | 0.849* | 0.897 | 0.0622 | 0.486*** | 0.0286 | 0.00110 |
| | (0.449) | (0.885) | (0.0602) | (0.183) | (0.126) | (0.00877) |
| Broadband Coverage | -129.9 | 414.7* | 36.96** | -44.45 | 540.8*** | 33.82*** |
| | (226.0) | (250.3) | (18.63) | (58.22) | (49.59) | (3.894) |
| Retail Space | -6,769*** | -1,985*** | -67.99 | -15,150*** | -5,992*** | -412.6*** |
| | (1,014) | (722.4) | (57.79) | (731.4) | (552.7) | (42.00) |
| Office space | -1,388 | -19,094*** | -1,281*** | -1,647** | -18,469*** | -1,301*** |
| | (1,095) | (1,125) | (87.45) | (762.4) | (601.7) | (47.12) |
| Retail space$^2$ | 24,200*** | -24,473*** | -1,604*** | 164,837*** | 47,503*** | 2,752** |
| | (4,737) | (3,958) | (359.9) | (18,988) | (14,373) | (1,163) |
| Office space$^2$ | 9,541* | 31,057*** | 2,042*** | 19,560 | 212,170*** | 16,917*** |
| | (5,424) | (6,278) | (529.9) | (21,376) | (8,964) | (880.5) |
| Observations | 1,828 | 1,828 | 1,828 | 5,331 | 5,331 | 5,331 |
| R-squared | 0.186 | 0.763 | 0.743 | 0.337 | 0.573 | 0.650 |

**Note:** OLS estimates of the association between neighbourhood characteristics and the elasticity $\eta_z$ defined in expression (5), the zoomshock $\Delta E_z$, (2), and the total effect on LPS employment $\tau_z$ (6) in each neighbourhood. All regressions also include local authority fixed effects; robust standard errors are reported in parentheses. $^{***}$denotes $p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. See the text for the definition of the RHS variables.

ing increased inequality.[11] The coefficients in the first three columns show no relationship between the IMD and the values of $\eta$, $\Delta E$, or $\tau$.

By contrast, Columns (5) and (6) and the pattern of blue dots in the north-west quadrant of Figure 4 suggest that, in positive neighbourhoods, these shocks are smaller in more deprived neighbourhoods. This implies that the benefits of increased demand for LPS will be higher in more affluent neighbourhoods. There is a

[11]The effect of the pandemic on distribution has been a concern since its outset (Blundell et al., 2020), both in advanced (Hacıoğlu-Hoke et al., 2021) and in developing countries (Sheng et al., 2022).

similar implication of the south-east plot in Figure 4. This reports the association between the total effect and the first of the two measures of housing we include, the average housing quality in the neighbourhood, computed from property tax assessments. This variable captures variations in the overall affluence of neighbourhoods rather than the left-tail of the neighbourhood income distribution as the IMD does. For this variable, there is no statistically significant relationship in areas with a negative zoomshock. In positive neighbourhoods the positive and significant effect on $\tau_z$ doubtless reflects the fact that those who live in areas with more desirable housing are likely more affluent and spend more on LPS, although the estimates in columns (4) and (5) are imprecisely estimated. Our second housing measure, housing "density" is the average number of people living in a dwelling: for given housing quality, and a low proportion of singles or pensioners. The table suggests that, in areas with more residents per household, the zoomshock is lower. There is also evidence that the elasticity is higher, although this estimate is less precise and not statistically significant. Together, these two effects mean that $\tau_z$ is lower. And so lower-income neighbourhoods will see larger declines or lower growth in LPS spending. Figure B.3 in the online appendix displays the associated binscatter plot.

A second set of covariates captures the ease of commuting from and working remotely in a given neighbourhood. The first of these is the neighbourhood population density, which we include to capture the idea that those in sparsely populated neighbourhoods may be less able to work remotely, due to reduced transport infrastructure, and greater distances, or reversing the direction of causality, people whose job does not require commuting may choose to live somewhere sparsely populated. We also include the average age of the residents, although this term will capture other ways in which these areas differ such as industrial composition.

Table 2 shows that the zoomshock is higher in more densely populated neighbourhoods. An increase in density is also associated with an increase in $\tau$. Our interpretation of these estimates is that the loss of employment is largest in areas with negative zoomshocks where there are relatively few residents. This confirms our intuition that city-centre neighbourhoods that have a mix of housing and office-space will be less affected. In positive neighbourhoods, density is associated both with a higher zoomshock, and with an increased overall effect. Since we include local authority fixed-effects, interpretation of this is that demand will be increased more in suburban rather than in more rural neighbourhoods. The north-east plot in Figure 4 shows that in fact the estimated relationships are similar for positive and negative neighbourhoods, but that there is much more noise in negative sub-sample.

A worker's age is also likely to be related to their ability to work remotely. We see that among areas with a negative zoomshocks neighbourhoods with an older average resident fare better. On the other hand, in areas with a positive zoomshocks an older population is associated with a smaller increase. This may reflect both the greater likelihood that younger workers can work remotely, and perhaps also their greater spending on LPS. [12]

The final set of covariates broadband speed and coverage, capture connectivity, although again these variables are likely to be endogenous to the geographical characteristics of a neighbourhood. They may proxy both proximity to an urban centre and the type of residents and businesses present in an area. Faster broadband is associated with a higher elasticity in all areas, although the effect is around twice as large in areas with a negative zoomshocks. Together with the lack of effect on the zoomshocks or $\tau_z$, this suggests the tentative interpretation that areas with fast broadband are most likely to also have a greater range of LPS available.

On the other hand, greater broadband coverage is associated with higher $\Delta E_z$ and $\tau_z$ in all neighbourhoods. Perhaps reflecting a sorting of those who can work remotely into areas with broadband. There is no effect of these variables in negative neighbourhoods, as might be expected given that broadband coverage varies little in them, see Table 1. Among positive neighbourhoods the impact is greater in areas with more and faster broadband. Taking all these results together, the interpretation for positive neighbourhoods is straightforward: the results are consistent with most commuters living in suburbia rather than rural areas. For negative neighbourhoods, our inference is that this effect is identified off those areas with negative zoomshocks which are not in city centres such as business parks where the surrounding areas may have poor broadband.

Another key way in which neighbourhoods vary is in the amount of retail and office

[12] Using other measures of the age distribution, such as the median, the proportion of pensioners or that of young people gives similar results.

space they include, and our final set of covariates captures exactly this. Areas with large amounts of retail space should be expected to have more of retail workers, for whom, typically, working remotely is not feasible. Likewise, areas with more office space are likely to employ many who can work remotely. It is useful to note, as shown in Table 1, that while the distributions of the two variables have similar averages, office space is much more concentrated, as one would indeed expect.

The results in Column (1) of Table 2 also suggest that the elasticity as well as the zoomshock is lower in negative neighbourhoods with more retail space. The results for office space are as would be expected. The coefficient on $\Delta E_z$ and $\tau_z$ are both negative suggesting, in line with expectations, that those who work in offices are more likely to commute and or more likely to be able to work remotely than other workers. Theoretical considerations (Duranton and Puga, 2020) suggest that agglomeration for both retail and office space should lead to non-linearities in the relation between floor space and employment in a given neighbourhood. This can be most easily evaluated by inspecting the binscatter plots in the south-west panels of Figure 4 and Figure B.3. These suggest limited evidence for non-linearities in retail space but the 95 percentile of the office space distribution is associated with a substantially higher increase in employment. For this reason, we also include quadratic terms in office floor space and retail floor space in Table 2.

# 4 Conclusion

Few know what the urban environment will look like in the future, but there is increasing agreement that it will be different from before the pandemic (Althoff et al., 2022; Rosenthal et al., 2022). The economy may move to a new equilibrium, where social norms and communication technology have changed sufficiently to ensure that remote work is a *normal* way of conducting many of the interpersonal professional interactions necessary in business. The ramifications of the changes to our way of working are complex. Policymaking will require an understanding of the externalities, positive and negative, caused by the shift to remote work on the parts of the economy not directly affected by it such as the transport and LPS industries, many of whose workers are among the lowest paid. In this paper we propose a method to study the effect of working remotely and apply it to the empirical analysis of employment on the retail and hospitality industry: this could be a template for the analysis of other industries with similar characteristics.

Among our main findings, is that the consequences of remote work for LPS demand in individual neighbourhoods are not only themselves extremely uneven with a few, largely city-centre, neighbourhoods seeing very large losses, and affluent suburbs more diffuse gains. But, also will tend to reinforce extant socio-economic inequalities. The neighbourhoods that stand to gain are those where fewer people live in better houses, with lower levels of deprivation. The interaction with the characteristics of neighbourhoods should be an important consideration for policymakers. For example, we find that the areas where LPS service demand has increased the most are those with relatively few suppliers due to low amounts of retail space and so expanding demand to create new LPS jobs in these areas may present additional difficulties and require new and imaginative policy solutions.

This analysis has important implications for policy. First, in the near future we will continue to see an adjustment in our local economies as post-pandemic working arrangements stablise and LPS businesses adjust. As our analysis shows, this will mean a movement of LPS demand from city centers to residential areas. For this demand to be realised as a market transaction, thereby avoiding LPS job losses, it is imperative that workers and businesses are able to move to where demand is located. A barrier to this may be in the form of infrastructure, including public transportation and commercial floor space. Second, our analysis provides first estimates reflecting how LPS business and workers are effected by where other workers spend their day. Metrics such as the LPS spending elasticity have implications for city design and place-based policies, providing a glimpse into the black-box of local employment multipliers.

# References

**Althoff, Lukas, Fabian Eckert, Sharat Ganapati, and Conor Walsh**, "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?," Working Paper, National Bureau of Economic Research August 2021.

**_, _, _, and _**, "The geography of remote work," *Regional Science and Urban Economics*, 2022, *93*, 103770.

**Autor, David and Elisabeth Reynolds**, "The nature of work after the COVID crisis: Too few low-wage jobs," *The Hamilton Project, Brookings*, 2020.

**Barrero, Jose Maria, Nicholas Bloom, Steven J. Davis, and Brent H. Meyer**, "COVID-19 Is a Persistent Reallocation Shock," *AEA Papers and Proceedings*, May 2021, *111*, 287–91.

**Blundell, Richard, Monica Costa Dias, Robert Joyce, and Xiaowei Xu**, "COVID-19 and Inequalities," *Fiscal studies*, 2020, *41* (2), 291–319.

**Brueckner, Jan, Matthew E. Kahn, and Gary C. Lin**, "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?," Working Paper, National Bureau of Economic Research March 2021.

**Casey, Abi**, "Office for National Statistics Website: Business and individual attitudes towards the future of homeworking, UK: April to May 2021," Jun 2021.

**De Fraja, Gianni, Jesse Matheson, and James Rockey**, "Zoomshock: The geography and local labour market consequences of working from home," *Covid Economics*, 2021, *64*, 1–41.

**_, _, Paul Mizen, James Rockey, Shivani Taneja, and Gregory Thwaites**, "Covid reallocation of spending: The effect of remote working on the retail and hospitality sector," Technical Report, Sheffield Economic Research Paper Series, 2021006 dec 2021.

**Dingel, Jonathan I. and Brent Neiman**, "How many jobs can be done at home?," *Journal of Public Economics*, 2020, *189*, 104235.

**Duranton, Gilles and Diego Puga**, "The Economics of Urban Density," *Journal of Economic Perspectives*, Aug 2020, *34* (3), 3–26.

**Hacıoğlu-Hoke, Sinem, Diego R Känzig, and Paolo Surico**, "The distributional impact of the pandemic," *European Economic Review*, 2021, *134*, 103680.

**Office for National Statistics**, "Business Structure Database, 1997-2018: Secure Access. 10th Edition. UK Data Service. SN: 6689," http://doi.org/10.5255/UKDA-SN-6697-10 2019.

—, "Annual Survey of Hours and Earnings, 1997-2019: Secure Access. 16th Edition. UK Data Service. SN: 6689," http://doi.org/10.5255/UKDA-SN-6689-16 2020.

**Ramani, Arjun and Nicholas Bloom**, "The Donut Effect of Covid-19 on Cities," Working Paper, National Bureau of Economic Research May 2021.

**Rosenthal, Stuart S, William C Strange, and Joaquin A Urrego**, "JUE insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19," *Journal of Urban Economics*, 2022, *127*, 103381.

**Sheng, Jaymee, Anup Malani, Ashish Goel, and Purushotham Botla**, "JUE Insight: Does mobility explain why slums were hit harder by COVID-19 in Mumbai, India?," *Journal of Urban Economics*, 2022, *127*, 103357. JUE Insights: COVID-19 and Cities.

**Taneja, Shivani, Paul Mizen, and Nicholas Bloom**, "Working from home is revolutionising the UK labour market," March 2021. Online; posted 15 March 2021.

# Appendix. For online publication.

## A Data

In this appendix we provide additional details on the data used in our analysis as well as some additional summary statistics.

### A.1 Calculating the zoomshock

Here we provide details on the method of De Fraja et al. (2021a) to calculate term as a *zoomshock*, the geographic change in economic activity due to the shift towards RW during the Covid-19 pandemic. As explained in section 2 the zoomshock reflects the difference between the number of workers who live in a neighbourhood, and can work remotely, and the number of workers who work in a neighbourhood, and can work remotely:

$$\left( \begin{array}{c} \text{Number of workers who } \textit{live} \\ \text{in neighbourhood } z \text{ and} \\ \text{can work remotely} \end{array} \right) - \left( \begin{array}{c} \text{Number of workers who } \textit{work} \\ \text{in neighbourhood } z \text{ and} \\ \text{can work remotely} \end{array} \right) \tag{A1}$$

In this paper we build on this measure to reflect the amount of post-pandemic RW that we expect to be done from home over what was done pre-pandemic. Specifically, we will compare expectations of the amount of work that will be remote in 2022 to estimates of the amount of RW in 2019. That is, we estimate the change in the amount of work done in a neighbourhood $z$ as:

$$\Delta E_z = \sum_o [(RW_{o,z}^{2022} - RW_{o,z}^{2019})E_{o,z}^R - (RW_{o,z}^{2022} - RW_{o,z}^{2019})E_{o,z}^W], \tag{A2}$$

where $RW^{2022}_{o,z}$ is the expected proportion of RW in 2022, for occupation $o$ and neighbourhood $z$; $RW^{2019}_{o,z}$ is the proportion of RW in 2019, for occupation $o$ and neighbourhood $z$; $E^{R}_{o,z}$ and $E^{W}_{o,z}$ are the number of workers with jobs in occupation $o$ who live and work in neighbourhood $z$ (pre-pandemic).

By changing where workers are spending their time, the increase in RW will also lead to a geographic change in where workers do their work-related spending on locally consumed services, particularly retail and hospitality. The demand for coffees, drinks, and sandwiches and retail shopping during lunch breaks, will be shifted from neighbourhoods in which workers work to neighbourhoods in which workers live.

We calculate this expected change in local retail and hospitality spending by weighting the geographic movement of work across different occupations by the average spending in each occupation and location. Formally the change in retail and hospitality spending in a given neighbourhood, $\Delta S_z$, is calculated as:

$$\Delta S_z = \sum_{o}[(RW^{2022}_{o,z} - RW^{2019}_{o,z})Spend^{2019}_{o,z}E^{R}_{o,z} - (RW^{2022}_{o,z} - RW^{2019}_{o,z})Spend^{2019}_{o,z}E^{W}_{o,z}] \tag{A3}$$

$Spend^{2019}_{o,z}$ is the average spending, while at work, by workers in occupation $o$ working in neighbourhood $z$ before the pandemic.

We use the information from the Work From Home Survey, described above, to estimate values for $RW^{2022}_{o,z}$, $RW^{2019}_{o,z}$, and $Spend^{2019}_{o,z}$ in Equation equation (A3). For each of the twenty-five survey occupation categories and four location described above, we calculate the average increase in WFH for 2022 over 2019, and the average work-related spending on retail and hospitality.

The 2011 population Census, published by Office for National Statistics, provides us with the pre-pandemic distribution of residents and workers by occupation and location, $E^R_{o,z}$ and $E^W_{o,z}$. These data provide, for every middle super output area (MSOA)[13], a count of the number of employees working in the MSOA by three-digit Standard Occupational Classification (SOC), and a count of the number of employees living in the MSOA by four-digit SOC. To match with the survey information, each SOC code is allocated to one of the 25 occupations (see data appendix for more details), average values of $RW^{2022}_{o,z}$, $RW^{2019}_{o,z}$, and $Spend^{2019}_{o,z}$ are assumed to be constant across MSOAs ($z$) within each of the four geographic regions we consider above. This means that cross MSOA variation in average spending and RW within one of the four geographic regions will be driven by variation in occupation composition.

We express both equation (A2) and equation (A3) as percentage changes. For equation (A2) this is done by dividing by the total pre-pandemic number of jobs done in neighbourhood $z$. For equation (A3) we divide by the total retail and hospitality spending for neighbourhood $z$. We calculate total spending for a neighbourhood $z$ as the total employment in retail and hospitality done (by workers and all other forms of spending) in the neighbourhood multiplied by the output per worker.

## A.2 Work From Home Survey

### A.2.1 Assignment of occupation

The Work From Home Survey asks respondents to choose from a list of 25 occupational categories plus "other", the occupation which best describes their job. Approximately 15% of survey respondents choose the "other" category and

[13] An MSOA is an official geographic unit used in England and Wales. Each unit defines a geographic area in which approximately 8,254 people reside. There are 7,201 MSOAs across England and Wales

entered in a description of their job. In these cases we used our judgment to allocate their written response to the most appropriate occupation category.

To match survey occupations to UK Standard Occupation Classification codes we assign three digit, and four digit, SOC codes to each of the 25 occupation categories. The industry where the residents of an area work is taken from the 2011 population Census published by Office for National Statistics;

### A.2.2 Pre-pandemic (2019) working from home

The survey does not directly ask how much work was done from home before the pandemic. Instead, we use information form two questions:

> *Q9: In 2019 (before COVID) approximately how many hours a week did you work when employed?*
> *Q57: Prior to the Covid-19 pandemic, how many full days were you commuting to work?*

Assuming an eight-hour work day, the number of days worked from home is calculated as

$$WFH^{2019}_{i,o,z} = \frac{\frac{Q9_{i,o,z}}{8} - Q57}{5} \tag{A4}$$

We then use these individual values to take the mean by occupation and location:

$$WFH^{2019}_{o,z} = \frac{1}{n_{o,z}} \Sigma_i WFH^{2019}_{i,o,z} \tag{A5}$$

where $n_{o,z}$ is the number of survey respondents in occupation $o$ and area $z$.

## A.3 Data sources

### A.3.1 Work and residential populations

The count of residents and workers by occupation and location, $E^R_{o,z}$ and $E^W_{o,z}$, comes from the 2011 national census, published by Office for National Statistics. These data provide, for every MSOA, a count of the number of employees working in the MSOA by three-digit SOC code, and a count of the number of employees living in the MSOA by four-digit SOC code. All data can be downloaded from Office for National Statistics NOMIS website.

### A.3.2 Neighbourhood retail and hospitality output

For Equation (4), we calculate the total spending on retail and hospitality for each MSOA as the total number of workers in the area multiplied by the average output per worker in each of the nine ITL1 regions, plus Wales. Data for output per worker is downloaded from the Office for National Statistics website.

How the shift from working in the office to working from home will impact coffee shops, retail and other locally consumed services depends on the importance of spending by workers as opposed to other sources. For example, the City of Westminster and the City of London look similar in terms of the number of workers, but due to its considerable attraction to tourists, Westminster spending overall is much less dependent on the local workforce than the City of London. Therefore, a 20% decrease in office workers will have different implications in Westminster than it will in City of London.

More broadly, the extent to which LS are consumed by commuters versus residents varies across MSOA not just due to the number and type of commuters and the number and type of residents but also idiosyncratic factors such as tourism, transport links, etc. In figure B.2, we show the distribution of spending shares across MSOAs. We can see that in most MSOAs commuters account for 15–40% of LS expenditure.

#### A.3.3 Business rates and floorspace

Business rates and commercial floor space data are reported by the Valuation Office Agency. All analysis reported in the main paper reflects 2019 values.

## B Additional Tables and Figures

In Figure B.1 we plot the increase in remote working in various occupations. Roughly speaking it suggests a positive correlation between pay and the potential for remote working.

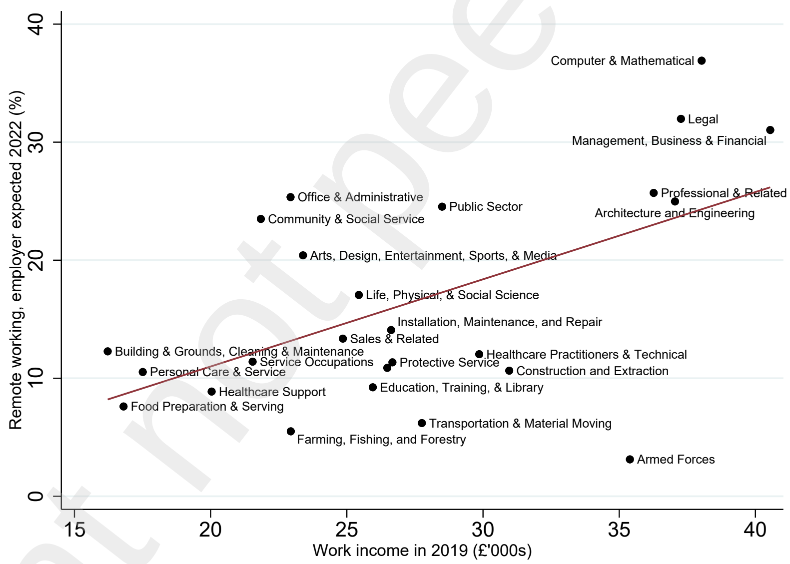
A more detailed report of this information is in Table B.1. This reports, for the various occupations and industries reported in the Working From Home survey, the percentage of time the respondents are on average able to work from home, classified by the part of England and Wales they live in. Outside London, we have divided the countries in the 15 next largest cities (local authorities) and the rest of England and Wales. The last column shows the p-value for a test of the hypothesis that work from home rates are the same across areas.

The next plot, Appendix B, shows the distribution of spending by people who spend their daytime working in a given MSOA. This changes both with the number of workers and with the amount they spend on average in each working day.

Figure B.3 shows the binscatter plots between RHS variables and the total effect of the zoomshock for the variables included in the regressions, but not plotted in figure 4, namely the average age and the average number of residents in a dwelling in the MSOA, the total floor space within its boundary, and the percentage of dwelling with broadband.

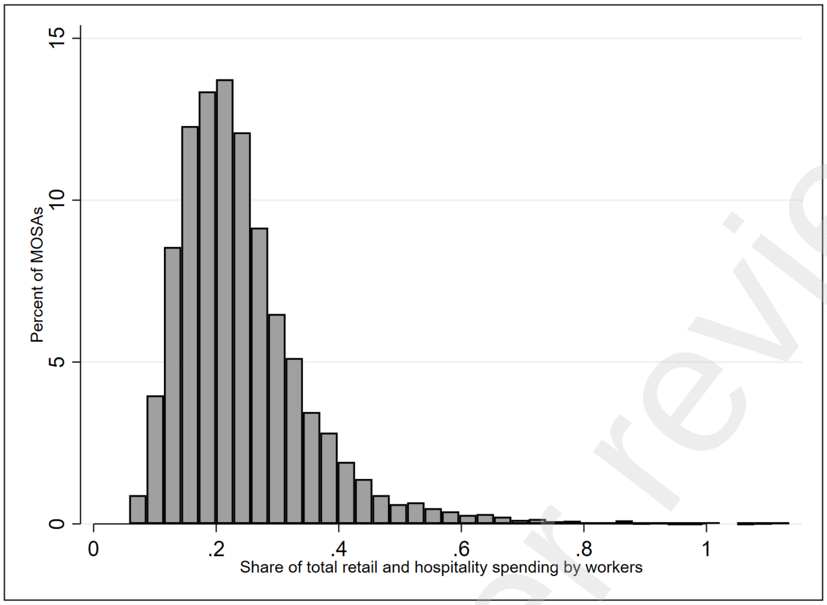
Finally, Table B.2 reports the output for the same regressions in Table 2, but expanding the sample to include *all* MSOAs, even those that, for the huge size of the zoomshock, can be considered extreme outliers. By and large the results are confirmed.

**Figure B.1:**
Change in working from home and income




Notes: This figures show a scatter plot of increase in remote working rates by occupation against income earned in 2019. All values are estimated from the Work From Home Survey.

**Figure B.2:**
Share of total retail and hospitality spending due to workers at work



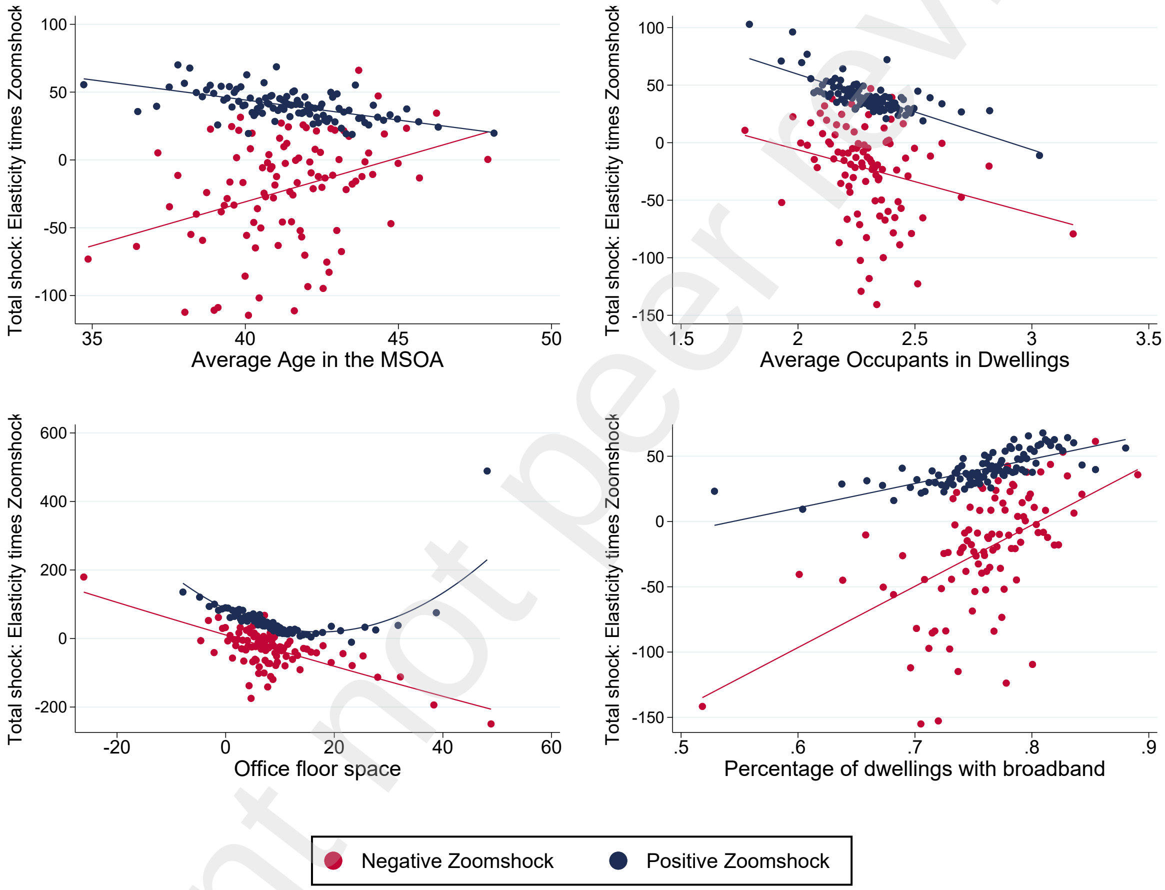

Notes: This histogram shows the distribution of neighbourhoods according to the share of total spending that is attributable to workers working in the MSOA.

**Table B.1:** Working from home, 2022 over 2019, by occupation and region

| Occupation | Smaller LAs | Large LAs | Central London | Outer London | *p-value* |
|---|---|---|---|---|---|
| Construction and extraction | 12.16 | 6.19 | 7.59 | 7.23† | 0.69 |
| | (2.56) | (5.62) | (3.43) | (3.09) | |
| Farming, fishing, and forestry | 6.38 | -5.36 | | | 0.35 |
| | (3.51) | (7.37) | | | |
| Management, business and financial | 26.83 | 40.65 | 39.70 | 39.25 | 0.00 |
| | (1.03) | (1.88) | (2.07) | (3.30) | |
| Office and administrative support | 22.68 | 34.35 | 33.35 | 32.78 | 0.00 |
| | (0.89) | (1.69) | (2.23) | (3.67) | |
| Production | 10.78 | 5.22 | 33.58 | 31.13 | 0.04 |
| | (1.63) | (3.68) | (8.47) | (11.72) | |
| Professional and related | 20.96 | 39.16 | 36.94 | 34.34 | 0.00 |
| | (1.40) | (2.88) | (2.51) | (5.00) | |
| Sales and related | 13.09 | 12.50 | 17.00 | 20.10 | 0.59 |
| | (1.12) | (2.40) | (3.43) | (5.16) | |
| Service | 9.78 | 19.98 | 8.20 | 18.59 | 0.05 |
| | (1.52) | (3.50) | (5.52) | (7.31) | |
| Transportation and material moving | 5.67 | 10.49 | 9.12 | 0.81 | 0.59 |
| | (1.36) | (3.27) | (12.30) | (1.02) | |
| Education | 8.22 | 13.98 | 13.01 | 17.21 | 0.02 |
| | (0.77) | (1.90) | (2.90) | (6.80) | |
| Public sector | 22.46 | 31.33 | 34.45 | 22.65 | 0.00 |
| | (1.22) | (1.97) | (3.51) | (4.38) | |
| Computer and mathematical | 37.10 | 40.84 | 28.55 | 36.93 | 0.19 |
| | (1.77) | (3.07) | (3.55) | (4.54) | |
| Architecture and engineering | 22.59 | 40.69 | 26.95 | 32.87† | 0.08 |
| | (2.62) | (5.84) | (14.13) | (10.09) | |
| Physical and social science | 19.38 | 14.39 | 36.47 | 6.64† | 0.10 |
| | (4.15) | (6.36) | (12.85) | (10.69) | |
| Community and social service | 21.50 | 32.05 | 39.58 | 29.18† | 0.22 |
| | (2.82) | (6.52) | (7.00) | (8.39) | |
| Legal | 26.48 | 42.30 | 31.71 | 37.54 | 0.04 |
| | (3.21) | (4.92) | (5.53) | (9.06) | |
| Arts, design, entertainment, sports, | 16.72 | 24.56 | 31.80 | 53.25 | 0.00 |
| and media occupations | (1.95) | (3.59) | (4.04) | (6.82) | |
| Healthcare practitioner and technical | 13.34 | 4.63 | 23.42 | 3.59 | 0.00 |
| | (1.29) | (2.18) | (3.77) | (10.68) | |
| Healthcare support | 8.17 | 10.98 | 22.60 | 9.91 | 0.28 |
| | (1.42) | (3.27) | (6.05) | (14.40) | |
| Protective service | 12.36 | 6.44 | 5.94† | 5.94† | 0.85 |
| | (4.09) | (5.58) | (6.36) | (6.36) | |
| Food preparation and serving | 8.51 | 2.28 | 3.58 | 3.42† | 0.54 |
| | (1.69) | (1.36) | (3.61) | (3.37) | |
| Cleaning and maintenance of buildings | 14.87 | 0.00 | 2.21 | 2.21† | 0.16 |
| and grounds | (3.48) | (0.00) | (2.80) | (2.80) | |
| Personal care and service | 11.14 | 2.60 | 4.43 | 3.62† | 0.89 |
| | (2.92) | (9.35) | (4.15) | (3.44) | |
| Installation, maintenance and repair | 15.87 | 7.51 | 0.00 | 2.94† | 0.61 |
| | (3.60) | (6.50) | (0.00) | (2.68) | |
| Correlation with telework index* | 0.75 | 0.78 | 0.58 | 0.59 | |
| $R^2$ of telework index | 0.56 | 0.61 | 0.34 | 0.35 | |

Notes: This table reports working from home rates by occupation and location of job (in 2019). *Smaller LAs* refers to all local authorities outside the Greater London area which are not in the top 15 cities by population size. The *Large LAs* are the top 15 largest local authorities by 2019 population size. Mean standard errors are reported in parenthesis. The column labelled *p-value* reports the p-value corresponding to a test of the hypothesis that work from home rates are the same across areas.
†Cells for which $n < 5$ have been replaced with averages for Greater London.
*Occupation telework index as calculated in Dingel and Neiman (2020)

**Figure B.3:**
Bin scatter plots of $\tau$, the LPS employment of the zoomshock.




**Note:** Each diagram is a bin scatter plot of the association of the variable on the horizontal axis with the total effect of the zoomshock on LPS workers, expression (6). The diagrams control for the other variables on the vector of controls in regression (7) and the local authority fixed effects.

**Table B.2:** All MSOA, including commercial and office districts

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | MSOAs with negative zoomshock | | | MSOAs with positive zoomshock | | |
| Effect on LPS employment | Elasticity | Zoom-shock | Total effect | Elasticity | Zoom-shock | Total effect |
| IMD | -1.088 | 0.808 | 0.0685 | -0.530* | -3.711*** | -0.229*** |
| | (1.204) | (1.610) | (0.143) | (0.294) | (0.199) | (0.0145) |
| Housing Quality | -105.7 | 104.4 | 7.225 | 21.98 | 21.35 | 5.932*** |
| | (73.46) | (142.5) | (12.63) | (21.12) | (16.33) | (1.206) |
| Housing Density | -25.42 | -325.3*** | -24.47*** | 0.417 | -176.0*** | -13.27*** |
| | (51.69) | (89.53) | (7.386) | (21.05) | (14.81) | (1.143) |
| Density | 0.573 | 6.759*** | 0.553*** | 0.531** | 1.700*** | 0.114*** |
| | (0.580) | (1.352) | (0.127) | (0.236) | (0.135) | (0.0112) |
| Average Age | -1.835 | 14.98* | 0.909 | -0.397 | -10.74*** | -0.789*** |
| | (4.142) | (8.049) | (0.665) | (1.529) | (0.979) | (0.0712) |
| Broadband Speed | 0.684 | 0.880 | 0.00948 | 0.486*** | 0.0286 | 0.00110 |
| | (0.435) | (1.229) | (0.114) | (0.183) | (0.126) | (0.00877) |
| Broadband Coverage | -167.4 | 699.2** | 62.96** | -44.45 | 540.8*** | 33.82*** |
| | (203.8) | (320.3) | (27.15) | (58.22) | (49.59) | (3.894) |
| Retail Space | -4,070*** | -6,085*** | -459.9*** | -15,150*** | -5,992*** | -412.6*** |
| | (653.2) | (760.4) | (64.74) | (731.4) | (552.7) | (42.00) |
| Office Space | 669.7** | -18,123*** | -1,332*** | -1,647** | -18,469*** | -1,301*** |
| | (272.0) | (1,564) | (144.9) | (762.4) | (601.7) | (47.12) |
| Retail space$^2$ | 6,670*** | 3,950 | 1,215*** | 164,837*** | 47,503*** | 2,752** |
| | (2,355) | (4,635) | (410.3) | (18,988) | (14,373) | (1,163) |
| Office space$^2$ | -76.99 | -7,097*** | -1,085*** | 19,560 | 212,170*** | 16,917*** |
| | (187.9) | (918.8) | (85.23) | (21,376) | (8,964) | (880.5) |
| Observations | 1,870 | 1,870 | 1,870 | 5,331 | 5,331 | 5,331 |
| R-squared | 0.183 | 0.981 | 0.984 | 0.337 | 0.573 | 0.650 |

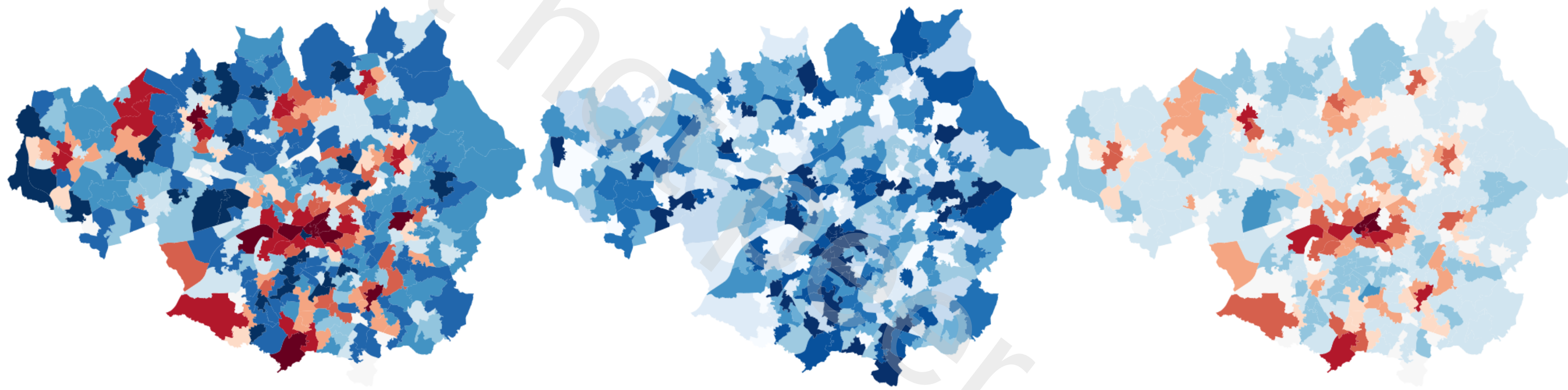
**Note:** This table corresponds to columns (1)-(3) of Table 2, but including also the 45 MSOAs that have experienced a negative zoomshock exceeding 5000 or a total impact exceeding 2000 in absolute value.

# C Additional Maps

In this section, we report additional maps, for some metropolitan areas of England, Manchester (this is the same map as in the text), Greater London, Birmingham and Leeds, as well as the entirety of England and Wales.

**Figure C.1:** Remote working and LPS workers: Manchester Figure 1 in the text.

**(a)** Zoomshock ($\Delta E_z$) **(b)** LPS elasticity ($\eta_z$) **(c)** Total effect ($\tau_z$)



*Note:* In the choropleth maps, each MSOA in Greater Manchester is coloured according to the quantile in which the corresponding variable falls in the ranking of the MSOAs. The leftmost map is the zoomshock, the middle one the LPS elasticity, and the rightmost the overall effect on LPS employment, $\tau_z$ in expression (6). Blue values are positive, red value negative, and a deeper shade indicate a higher value in absolute terms.
*Data source:* ONS Business Structure Database, 2018. Proportion of homework by MSOA based on authors calculations using information from the ONS Annual Survey of Hours and Earnings, 2017, 2018, 2019, and the Working from Home Survey 2022.

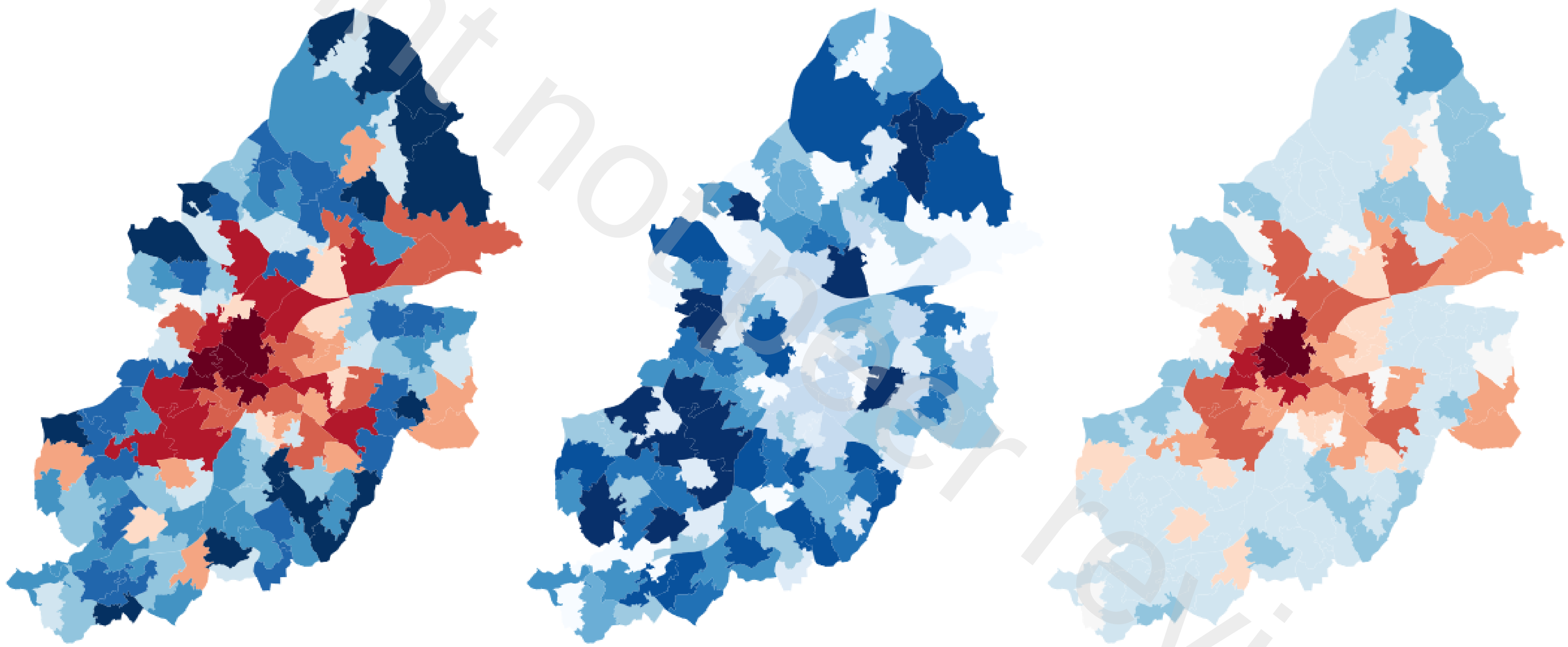
**Figure C.2:** Remote working and LPS workers: Greater London

**(a)** Zoomshock ($\Delta E_z$) **(b)** LPS elasticity ($\eta_z$) **(c)** Total effect ($\tau_z$)

*Note:* In the choropleth maps, each MSOA in the Greater London is coloured according to the quantile in which the corresponding variable falls in the ranking of the MSOAs. Other details as for figure C.1.

Figure C.3: Remote working and LPS workers: Birmingham

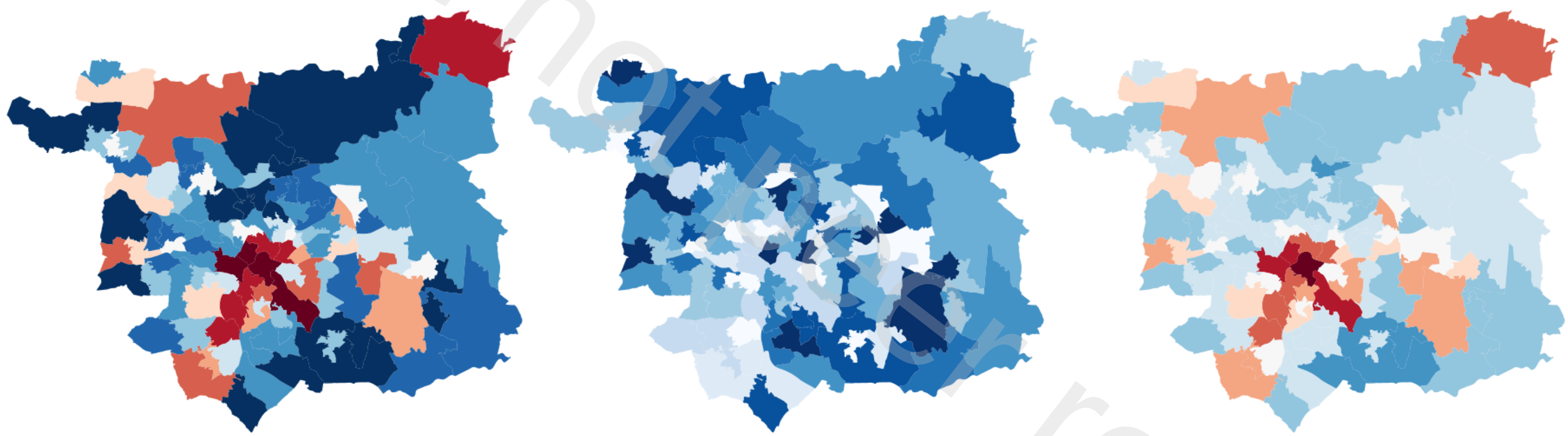
**(a)** Zoomshock ($\Delta E_z$) **(b)** LPS elasticity ($\eta_z$) **(c)** Total effect ($\tau_z$)



*Note:* In the choropleth maps, each MSOA in the City of Birmingham is coloured according to the quantile in which the corresponding variable falls in the ranking of the MSOAs. Other details as for figure C.1.

Figure C.4: Remote working and LPS workers: Leeds

**(a)** Zoomshock ($\Delta E_z$) **(b)** LPS elasticity ($\eta_z$) **(c)** Total effect ($\tau_z$)



*Note:* In the choropleth maps, each MSOA in the Greater Leeds region is coloured according to the quantile in which the corresponding variable falls in the ranking of the MSOAs. Other details as for figure C.1.