Remote working and the new geography of local service spending.[||]

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Abstract

Remote working has rapidly become the new norm in many sectors, at least some of the time. Remote working changes where workers spend much of their time and the geographical location of demand, particularly for local personal services (LPS). Our main contribution is to systematically quantify this change for England and Wales using a new nationally representative survey of nearly 35,000 working age adults, which captures (pre-pandemic) LPS spending while at work and permanent changes in remote working. On average, our work shows neighbourhoods where people commute 20% less often experience a decline in LPS spending of 5%. There is a clear geographic pattern (the "donut" effect) to these spending changes but our granular analysis shows that they are uneven: large decreases in LPS demand are concentrated in a small number of city-centre neighbourhoods, while increases in LPS demand around the periphery are more dispersed. Further analysis of neighbourhoods by geographical and socio-demographic characteristics shows the least affluent are most likely to benefit the least from remote work, increasing inequality.

Keywords: Remote working, Work-from-home, Local labour markets, Local personal services, Retail industry, Hospitality industry.

JEL Classifications: R12, J01, H12.

1 Introduction

In this paper we make use of a unique combination of census data, administrative data, and a new survey of working age adults to predict the medium term consequences of the rise of remote working on the geography of work and on the pattern of employment in the industries providing *local personal services* (LPS). These are goods and services which require the presence of a worker for the purchaser to benefit from their consumption.[1] Since these were previously located between home and work or around the workplace they were concentrated in city centres and near transportation. The move to remote work has dispersed the customer base, in ways that we conjecture may have lasting effects. We show that these will likely be spatially extremely uneven and so will affect geographical inequalities and will require policymakers to consider the implications and counter them.

We focus here on the subset of these services which are purchased and consumed wherever people *are physically present*, rather than where they live. By altering where people spend their working time, remote working also alters the location where they purchase the LPS they consume during their working time and the time they travel to work. Thus, we focus on mid-morning coffees, sandwich lunches, haircuts, after work drinks, work related taxi rides, and so on, but not construction, repair, domestic cleaning, gardening, or dog walking. 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. Our focus is on the effects of the changes determined by some workers' increased ability to work remotely. We assume away changes in shopping habits and tourism patterns.

We use a new, nationally representative, survey of nearly 35,000 UK workers. The survey provides information on the respondents' remote working before the 2020 pandemic and on their retail and hospitality expenditure at or near their work-

[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".

place before the 2020 pandemic, as well as their employers' plan and their own preference to work remotely after 2022, and the locations of both their home and work. We combine this information with census data, reflecting the distribution of where all workers work and where they live, and apply the methodology proposed by De Fraja et al. (2021) to estimate the potential post-pandemic change in retail and hospitality spending due to remote working across 7,201 neighbourhoods in England and Wales.

We document three important findings. First, the increase in remote working and the corresponding shift in the geography of work will be persistent and large enough to have substantial effects on the geography of LPS spending patterns. In line with medium term predictions of employers (Barrero et al., 2021b) we predict that the percentage of work done remotely will be 20 percentage points above its pre-pandemic level. This augurs a substantial shift of workers away from office-dense city centres to residential suburbs.

Second, this average masks a considerable geographical dispersion which will have substantial effects on LPS workers, who account for approximately 20% of the labour force. We should expect a stark asymmetry between gains and losses: employment losses will be dramatically concentrated in city centres, while increases in the demand for workers are spread across many residential suburbs and smaller commuter towns. For example, one central London neighbourhood with a residential population of 9,721, is expected to lose 8,000 LPS jobs. This loss is equivalent to the total increase in LPS jobs across the 161 largest-gaining neighbourhoods, with a combined population of over 1.55 million. Importantly, the effect is highly variable: our fine-grained geographical analysis shows how these effects often vary dramatically even among seemingly similar neighbouring locations.

Third, we show that the distribution of employment gains and losses depends not only on the *size* of the pre-pandemic workforce, but, importantly, on the different patterns of workers' spending on LPS. To quantify this effect, we compute an important metric, the *LPS spending elasticity*. This measures the percentage change in LPS spending which follows a percent change in the amount of work done in each given neighbourhood. Our estimate of this measure is on average 0.246, suggesting that a 20% decrease in the number of workers commuting into a given neighbourhood is expected to decrease LPS spending by about 5% (0.246 $\times$ 20%).

But again this average value masks considerable variation across the country. While most neighbourhoods have values between 0 and one half, the elasticity is notably higher, approaching one, in neighbourhoods, such as financial districts, where tourists and shoppers are few and workers' spending is a very large portion of overall spending on LPS. Our estimates of this elasticity will assist policymakers intending to quantify the effects that place-based policies to reallocate workers within urban centres might have on spending in each localized neighbourhood.

As an application of our analysis, we conclude the paper by identifying the variables associated with the components of a neighbourhood LPS spending shock. Awareness of the predictors of the severity of these shocks is an essential ingredient to policymaking. 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 fine details of the effects of these factors will be a crucial input in the design of granular interventions, but the general message that emerges from this part of the 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., 2021b, 2023) and updates earlier estimates for the UK (Casey, 2021; Meyrick, 2022). We also build on previous work on how remote working will affect where work is done in the UK (De Fraja et al., 2021; Matheson et al., 2021; Nathan and Overman, 2021), and the US (Ramani and Bloom, 2021; Althoff et al., 2022; Brueckner et al., 2021). Previous studies have noted the impact that the rise in remote working will have on LPS spending for urban centres for the UK (De Fraja et al., 2021) and for the US (Althoff et al., 2022). Using data from the US counterpart to our survey, (Ramani and Bloom, 2021) estimate that LPS spending will drop by 13% in Manhattan and 4.6% in San Francisco due to remote working. These estimates mirror our findings for major UK centres such as London, Birmingham, and Manchester.

In this paper we make three important contributions to this literature. First, in contrast to US studies Althoff et al. (2022); Chetty et al. (2023), is that we are able to observe the pre-pandemic distribution of workers at a very granular level by *both* place of work *and* place of residence. This allows us to calculate the potential change in spending in very small neighbourhoods, as opposed to aggregate spending shifts for the entire urban centre or for large rural areas. We can therefore map both the neighbourhoods which lose and the neighbourhoods which win, in terms of LPS spending, and highlight the dispersion of LPS demand, even between neighbouring areas, with obvious importance for policy decision with highly localised consequences, such as bus routes, location of primary schools, GP practices, and so on. Second, we use this framework to calculate the LPS spending elasticity which is of general importance. This elasticity reflects how neighbourhood economies are affected by changes in the *working* population. Our estimates provide the first calculation of an elasticity, reflecting highly localized multiplier effects. Third, unlike the previous work of De Fraja et al. (2021), our access to novel survey data allows us to calculate, for England and Wales, the percentage change in remote working relative to pre-pandemic levels and the accompanying percentage change in LPS spending.

The metrics that we estimate thus provide a valuable baseline for quantifying both the effect of remote working on LPS spending, and the sensitivity of LPS spending to large shifts in a neighbourhood's daytime productive activities. However, we note that they are perhaps conservative in several respects. First, our measures and assumptions are designed to isolate changes in LPS spending due to the shift to remote working; we do not measure changes that may arise from other channels such as post-pandemic changes in retail or tourism. Second, our measures reflect changes in neighbourhood LPS spending when spending is independent of where one works; in reality we may expect workers to reduce their LPS spending when they work from home. Therefore, our estimates likely reflect an optimistic scenario for overall LPS spending. Finally, we do not consider changes that workers choose to make about where they live as a result of remote work. While some US evidence suggests that remote workers may relocate from living in urban centres to suburbs or lower-productivity towns and cities (Brueckner et al., 2021; Gupta et al., 2021), we show below, Section 3.2, that relocation decisions driven by remote working are, as yet, of limited extent in the UK.

The remainder of the paper is structured as follows. Section 2 outlines our conceptual framework. Section 3 presents our results, and 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 where the LPS are consumed. 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 ρ_i^t, the remote workability index, measures the percentage of worker i's job done remotely in the two years. This is the measure adapted to the UK by De Fraja et al. (2021) from the measure constructed by Dingel and Neiman (2020) for the US. 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. 2021) 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 ΔE_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:

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

It is important to note that (4) implicitly defines ΔS_z^t as the geographic shift in *potential* retail and hospitality spending by workers, as it does not the higher likelihood of constraints in the supply LPS available in residential neighbourhoods, especially in rural or sparsely populated ones.

There are two assumptions which data limitations impose and which must be noted to interpret correctly (4) as the LPS spending change in neighbourhood z.

First, we assume that the amount of spending on retail and hospitality which workers would like to do does not change when workers work remotely as opposed to working in an office, and that it is spread evenly throughout the week. 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 potential 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 potential spending is independent of where work takes place. This assumption implies that actual local spending on entertainment will be affected only by constraints on supply. By the same token, the proportion of work/home LPS expenditure may itself vary: some people may enjoy after work drinks in a bar with colleagues once a week whether they work five or two days in the office (Thursday is the new Friday, and all that), 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.

Second, we assume that people do not move because of their ability to work remotely, so that both the number and the characteristics of people residing and remote working in each neighbourhood is the same pre- and post-Covid. While there is anecdotal evidence of remote workers moving with their families to idyllic locations both rural and digitally connected, where large gardens and languid sunsets replace traffic congestion and frantic commutes in dreary trains, we assume these cases to be rare and unrepresentative.

Some stylised evidence does indicate these assumptions to be reasonable: for example, Figure B.3 in the online appendix suggests that the change in the Google index of retail activity is positively correlated with the potential change in spending on LPS computed according to (4). In the same appendix, we also show, Figure B.4, the Pret A Manger Index (Office for National Statistics, 2024), which records transactions from approximately 400 Pret A Manger coffee shops around the UK. This is very specific data, but the trend is strikingly in line with our view of the link between remote work and spending in LPS. From around one year after the start of the pandemic, weekly till transactions stabilise in London suburban locations at a level consistently higher than in the month immediately preceding the lockdown, while they stabilise well below this level in locations which are near where City workers have offices. Of course changing our assumptions may alter our results, therefore we interpret our estimates as benchmark cases: it is relatively easy to see how alternative assumptions would change the size of the effects. For example if workers reduce by one third their LPS expenditure when they work remotely, then our estimated "gains" in the residential neighbourhoods will be correspondingly reduced. However, in Section 3.2 we provide more rigorous evidence that confirms the plausibility of our assumptions.

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

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

In the above, Ω_z^{2019} is the expenditure in 2019 by people who neither work nor live in neighbourhood z: tourists, shoppers, and so on. Including this is important as it captures the fact that in some neighbourhoods the demand for LPS will not be entirely driven by remote work but depends on other sources of demand for LPS. In such areas the elasticity of remote working will be smaller. Of course, Ω_z may have changed in some neighbourhoods between 2019 and 2022, and thus our estimated elasticities are the elasticity of remote working given 2019 levels of other sources of neighbourhood LPS demand.

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 τ_z where:

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

In (6), ϕ 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 ϕ 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 Calculating the zoomshock

We compute values for expressions (2), (5), (6) by combining our unique data from the *Survey of Working Arrangements and Attitudes for the UK (SWAA-UK)* with pre-existing Census data.

The *SWAA-UK* has collected information from around 2,500 (different) British adults each month since January 2021.[2] Using these data we construct, for 16 occupations and geographies,[3] an index of remote working in 2019 and 2022, ρ_i^{2019} and ρ_i^{2022} in our notation.[4]

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. Our geographical areas are Middle Super Output Areas, MSOA, a geographically meaningful census tract averaging $8,254$ residents, defined by the Office for National Statistics. There are $7,201$ MSOAs across England and Wales. For every MSOA, these data provide 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 data, each SOC code is allocated to one of the 25 occupations (see data appendix for more details). This allows us to calculate, $E^R_{o,z}$ (respectively $E^W_{o,z}$) as the number of workers with jobs in occupation o who live (respectively work) in neighbourhood z (pre-pandemic).

Next we define $\overline{\rho}^t_{o,z}$ as the average of ρ^t_i in each occupation and neighbourhood in a given year t. This is assumed to be constant for each occupation across all neigh-

[2] We include a full description of the survey in appendix A. Survey participants are UK residents aged between 20 and 64, 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] These are "Inner London", "Outer London", the largest 15 urban areas in England and Wales, the rest of the country; the approximate percentage of respondents in each is 3.5, 8.3, 17, 71.2.

[4] We compute the values of ρ^t_i 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.1.2), 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 ρ_i^{2022} to be the answer to the latter if the respondent is an employee, to the former if they are self-employed.

bourhoods (z) within each of the four geographic regions we consider above for a given year. This means that cross neighbourhood variation in average spending and remote working within one of the four geographic regions will be driven by variation in occupational composition.

Using these data and the method of De Fraja et al. (2021) we calculate what they term as a *zoomshock*, the geographic change in economic activity due to the shift towards remote working 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 now work remotely, and the number of workers who work in a neighbourhood and now work remotely. For both, this number is weighted by the index ρ_i.

Formally, we can expand (1) to compute the change in the amount of work that can be expected to be done remotely in the "post-pandemic long term" relative the the amount that was done pre-pandemic in neighbourhood z as: Office for National Statistics (2024)

$$\Delta E_z = \sum_o \left[\left(\overline{\rho}_{o,z}^{2022} - \overline{\rho}_{o,z}^{2019}\right) E_{o,z}^R - \left(\overline{\rho}_{o,z}^{2022} - \overline{\rho}_{o,z}^{2019}\right) E_{o,z}^W \right], \tag{7}$$

where $\overline{\rho}_{o,z}^{2019}$ and $\overline{\rho}_{o,z}^{2022}$ are defined, as above, as the expected proportions of remote working in 2019 and 2022, for occupation o and neighbourhood z.

This calculation thus combines our *SWAA-UK* based index of remote-work by occupation and region with precise census data on the number of workers of each occupation living and working in each neighbourhood to compute our granular measure of the zoomshock based on actual patterns of remote working.

By changing where workers are spending their time, the increase in remote working 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 remote workers work to neighbourhoods in which they live.

To compute in detail the expected change in local retail and hospitality spending in a given neighbourhood defined in (4), ΔS_z, we weight the geographic movement of work across different occupations by the average spending in each occupation and location. Formally, ΔS_z, is calculated as:

$$\Delta S_z = \sum_o [(\bar{\rho}_{o,z}^{2022} - \bar{\rho}_{o,z}^{2019}) S_{o,z}^{2019} E_{o,z}^{R} - (\bar{\rho}_{o,z}^{2022} - \bar{\rho}_{o,z}^{2019}) S_{o,z}^{2019} E_{o,z}^{W}], \tag{8}$$

where $S_{o,z}^{2019}$ is the average spending, while at work, by workers in occupation o working in neighbourhood z before the pandemic. Again we assume that this is constant, for each occupation, across neighbourhoods within each of the four geographic regions.

We express both equation (7) and equation (8) as percentage changes. For equation (7) this is done by dividing by the total pre-pandemic number of jobs done in neighbourhood z, E_z^{2019}. For equation (8) we divide by the total retail and hospitality spending for neighbourhood z, $S_z + \Omega_z$. We do not have MSOA data about total spending in retail and hospitality. Instead, 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 occupational average output per worker in that region.[5]

3.2 Preliminary empirical analysis

When presenting the conceptual framework we highlighted two important assumptions underpinning it. While the focus of the paper is on the effects of the zoomshock, it is nevertheless important to satisfy the reader that these assumptions do have an empirical foundation.

Our first regards the balance of home/work of LPS spending, changing of which we posited to be unrelated to the extent of remote working To investigate this, we

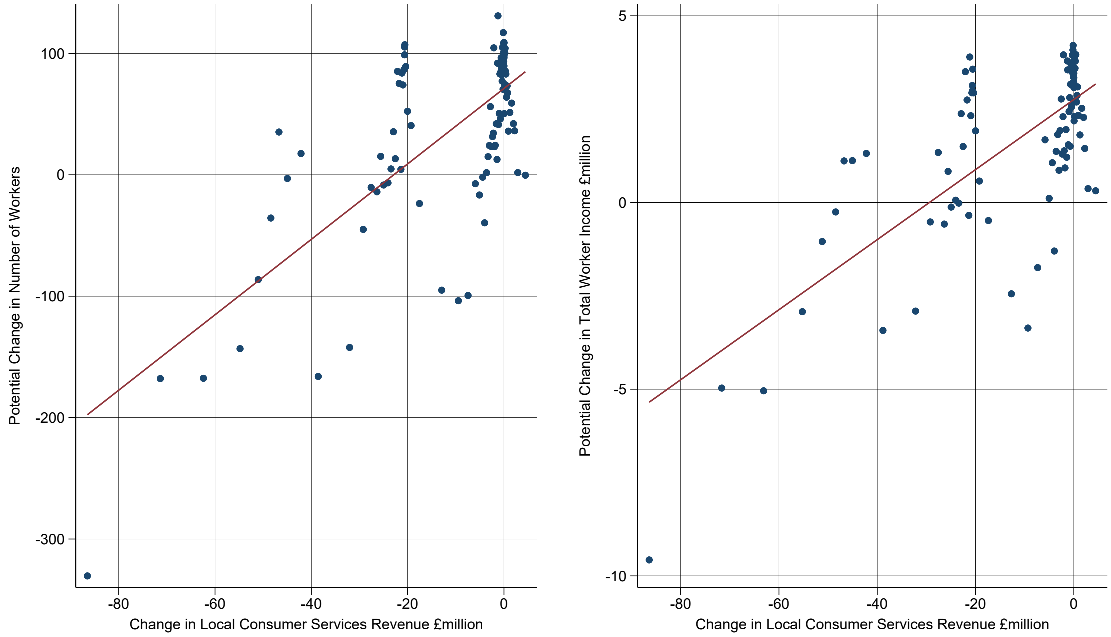
[5]Further details are provided in appendix A.2.2. This assumption implicitly assumes that productivity at home is unchanged for remote working. The evidence in this respect is mixed: some papers, mainly based on routine relatively low skill jobs (Atkin et al., 2023), suggest lower productivity, which may be counterbalanced by longer hours, with limited affect on output (Gibbs et al., 2023), but other works suggests increases in productivity of remote working as workers become used to it (Morikawa, 2023), or higher productivity than in the workplace (Alipour, 2023; Parravicini and Graffi, 2023). Particularly relevant for the present paper, a large UK study shows heterogeneous effects, with "productivity advantage experienced by those in 'good jobs' (in large firms, with managerial duties and high earnings)" when working from home (Burdett et al., 2023). In addition, a separate literature suggests substantially higher productivity for flexible work (Boltz et al., 2023).

combine data on the zoomshock, (2), from De Fraja et al. (2021), which is based on the Annual Survey of Hours and Earnings (Office for National Statistics, 2023a) with data on revenue received by establishments providing LPS, obtained from the the Business Structure Database (Office for National Statistics, 2023b). We expect a positive relationship between these measures to hold unconditionally, and so we feel justified in using a binscatter plot which provides a fully non-parametric estimate of the conditional mean function. Figure 1 presents two versions of the plot. In both panels the horizontal axis measures the change in LPS revenue (in £million) from 2019 to 2022, obtained from the BSD. The vertical axis on the LHS panel, measures the potential change in the number of workers actually spending the day in the neighbourhood, measured by (2); on the RHS, we compute the potential change in their expenditure, adding a further layer of assumptions. The similarity of the patterns in the two panels is suggestive that any change in spending pattern is not demonstrably violating the assumption we made above, namely, that it is qualitatively similar across MSOAs. Both panels show a clear positive relationship: the decline in LPS revenues is smallest in neighbourhoods where the daytime population has increased most due to working from home. Unsurprisingly, and in line with ample evidence available from a wide variety of source (for example, Dube et al. (2021)), the overall impact of remote working on LPS consumption is negative: in most areas, any increase in the number of workers spending their working day and purchasing LPS there is likely to have been swamped by the so-called cost of living crisis and labour shortages which led to an overall decline in revenues in the LPS sector.

Also important is to justify our second assumption in Section 2, that workers do not move because they can now work remotely, in view of some recent evidence from housing markets in the US (Gupta et al., 2021; Althoff et al., 2022; Brueckner et al., 2021) and to some extent the UK (**?**), that remote working may lead people to relocate their place of residence, and specifically, that they move away from urban centres to suburbs and less-productive towns and cities.[6] This pattern would exacerbate the qualitative patterns that we document if confirmed for England and Wales. However, recent UK data (Office for National Statistics, 2023a) suggests that remote working has at most a very weak association with long distance relocation

[6] Evidence to the contrary comes from analysis of Facebook usage, which is unlikely to be used while at work, and that has returned to pre-pandemic patterns **?**.

Figure 1:
Locally Consumed Services Revenue and Employment and Remote Work Potential



Note: Each figure is a binscatter plot relating the zoomshock to changes in locally-provided service sector revenue by MSOA. The left-hand plot relates potential change in the number of workers to the change in revenue. The right-hand plot relates the potential change in total worker income. Revenue are from the Business Structure Database (Office for National Statistics, 2023b) and zoomshock data from De Fraja et al. (2021). The solid line describes the line of best fit.

decisions. Figure B.5 in the online appendix suggests that any post-lockdown change in the trend of the number of employees who have moved to a different local authority, relative to its pre-pandemic value is very small. Moreover, it is also mirrored in changes in the trend in the numbers of employees whose house address changed at smaller areas of geographical aggregation, where moves are at most a few miles in most cases, and hence unlikely to be caused by the newly found ability to work remotely. We complement this evidence of lack of a clear trend in the unconditional probability of moving with with the estimation of a difference-in-difference model in which we compare the period before and after Covid-19: the treated group are the employees whose job can be done remotely. We restrict the sample to those who have *not* changed job, as the move may have been due to the job change, not the ability to work remotely. Formally, we estimate

$$M_{jt} = \beta_0 \text{covid}_t + \beta_1 \rho_j^t + \alpha \text{covid}_t \times \rho_j^t + \beta X_{jt} + \varepsilon_{jt} \tag{9}$$

Table 1:
Propensity to move and remote working potential

	(1) New MSOA	(2) New OA	(3) Not London	(4) Ind. FE
RemoteWork × PostCovid	0.003	0.004	0.002	0.002
	-0.007	-0.006	-0.006	-0.005
Observations	227,608	227,608	194,622	100,543
R^2	0.16	0.17	0.17	0.6
Fixed Effects	TTWA	TTWA	TTWA	Individ.

Note: Difference in Difference estimates of the impact of the zoomshock on changing residential location. In the specifications in Columns (1), (3), and (4) the dependent variable is a categorical variable denoting a house move to a new MSOA. In Column (2) is a move outside the "Output area". The coefficient of interest is that of $\text{covid}_t \times \rho^t_j$, that is α in (9). The controls and fixed effects included in all regressions are described after (9) in the text. 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.

where $t = 2016, \ldots, 2022$, M_{jt} is a categorical variable taking value 1 if the worker lives in a different geographical area from the previous year, covid_t is a categorical variable taking value 0 if $t \leq 2019$ and 1 otherwise, ρ^t_j is the Dingel-Neiman index for individual j in year t. The vector of control variables X_{jt} includes travel-to-work-area × year fixed effects to control for local labour market shocks, and industry × occupation fixed effects, age × gender dummies, and a quadratic in income. Standard errors are clustered by TTWA and year.

The estimation of (9) is reported in Table 1. In the first column the geographical area is the MSOA, the level we focus here. Other things equal, individuals able to work remotely were just over 0.3 percentage points more likely to move MSOA. This estimate is not statistically significant at conventional levels. The estimates for other geographical levels are also not statistically different from zero either: results for whether they have moved output area, which effectively means moving house at all, are reported in Column (2), and other geographies in Table B.2 in the appendix. The next two columns reproduce the results of Column (1) excluding workers residents in London, Column (3), and including an individual fixed effect, Column (4).

Overall, Table 1 and the related further analysis in the online appendix suggests that while working remotely has changed the pattern of LPS expenditure, it has not changed to any noticeable extent residential location decisions. This is consistent, for example, with location choices being largely determined by preferences for living in or outside of cities, or close to friends and family, rather than ease of commute. In the future, a longer time series will permit analysis of location choice with a possible focus on different subsets of the workforce.

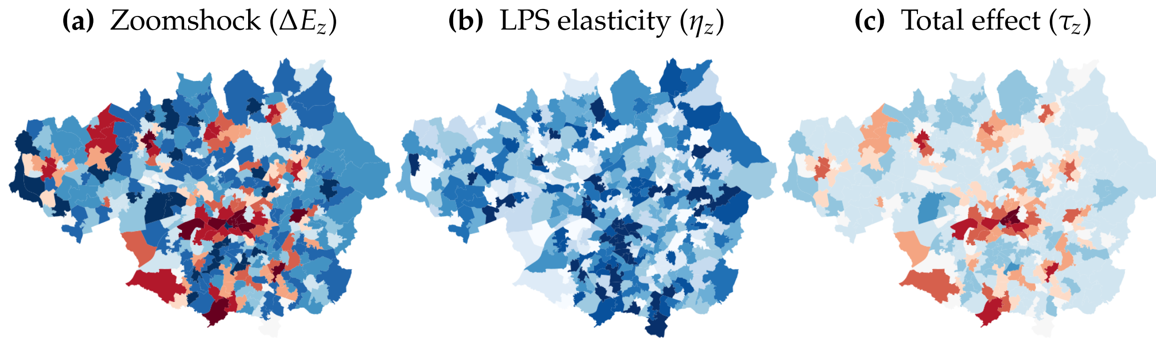
3.3 Results: Distribution of the zoomshock and the LPS elasticity

As anticipated, our measures of the effects of remote working vary widely from neighbourhood to neighbourhood. We illustrate this in Figure 2, which plots ΔE_z, η_z, and τ_z for each neighbourhood in the Greater Manchester metropolitan area. 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.

In addition to a British version of the "donut effect" Ramani and Bloom (2021), whereby activity moves from the centre to the periphery, all three maps show a pattern of neighbouring areas with sharply different colours, indicating how neighbourhoods 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 3.4. 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 η_z, is sharply different. Neighbouring areas which are filled with

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

Figure 2:
Remote working and LPS workers



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, τ_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 SWAA-UK 2022.

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 2 reports its average in England and Wales to be 0.246, similar for neighbourhoods with a negative or a positive zoomshock. The table also reports summary statistics for variables which will be discussed in Section 3.4.

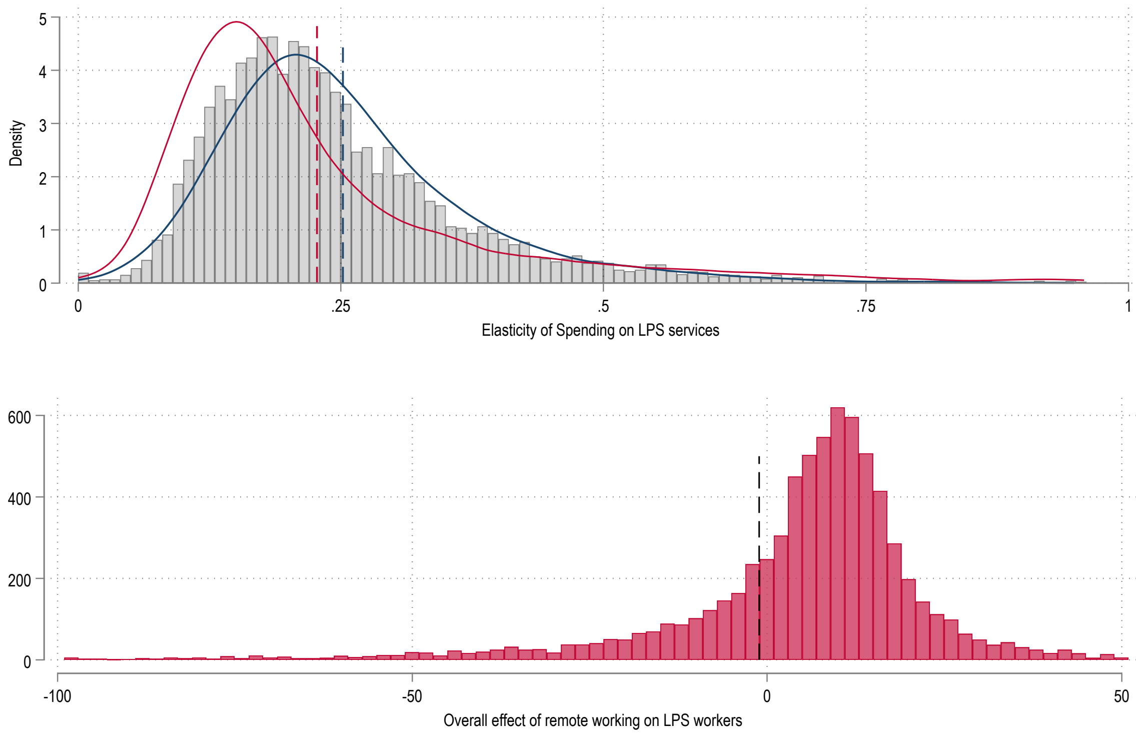
In Figure 3 we report the distribution, across all MSOAs in England and Wales, of the elasticity η_z, in the upper part of the diagram, and the shock ΔE_z, in the lower part. There are 99 MSOAs where the weighted net outflow of workers exceeds 1000, nine of which over 10,000, among them the City of London, 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 horizontal 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 LPS 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.

Here, as throughout, we are focusing on the benchmark of potential LPS spending not changing for someone working remotely. If, as discussed in Section 2, their actual LPS spending were in fact to decrease, then it is easy to see that the increase in spending in residential neighbourhoods would ne lower, shifting the distribution of elasticities in the upper panel of Figure 3 to the left. This would have two key consequences. First, the estimated magnitude of the zoomshock in areas with a net inflow of workers would be smaller. Second, it may mean that neighbourhoods for which we estimate a small increase in LPS spending might now see a decrease. Detailed data on the impact of remote working on spending on LPS will in future allow the estimation of deviation from this benchmark.

Figure 3 also depicts the kernel density estimates of the distribution of η_z disaggregated by whether 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 explored further in **?**.

The lower diagram in Figure 3 reports the distribution of the total effect τ_z. Most neighbourhoods experience an increase in demand for LPS, even though the mean of τ_z, indicated by the vertical dashed line, is negative. This reflects the concentration of reductions in demand in comparatively few neighbourhoods. Table 2 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 η_z and ΔE_z are positively correlated in neighbourhoods with positive zoomshocks, but only weakly negatively correlated in those with negative zoomshocks.

Figure 3:
The effect of the zoomshock on LPS employment.

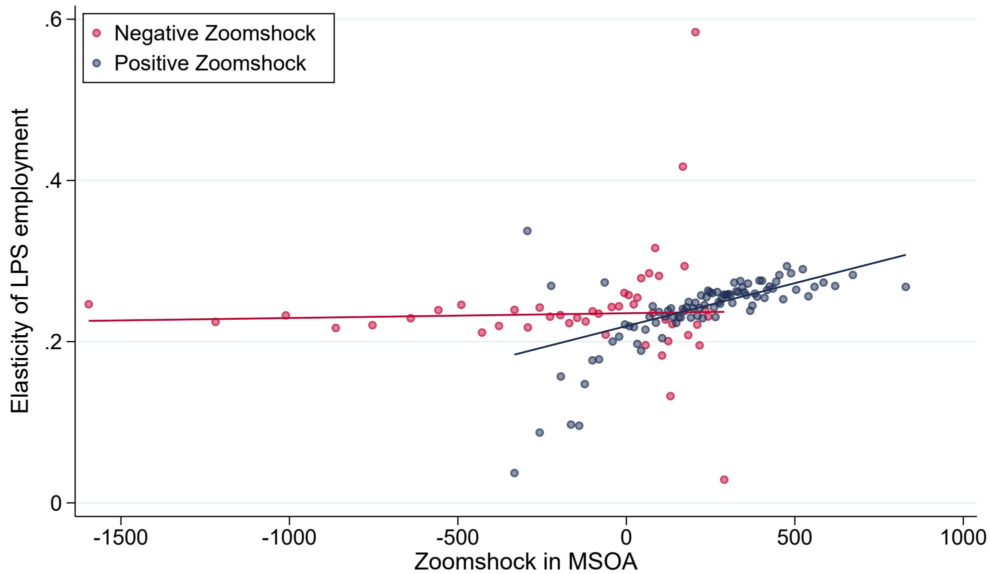


Note: The upper figure provides a histogram describing the distribution of elasticities, η_z, across neighbourhoods (MSOAs) in England and Wales: the width of each bin is 0.01. It also plots kernel density estimates of the distributions for MSOAs with positive (blue curve) and negative zoomshocks (red 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.

Figure 4 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.

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

Figure 4:
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).

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 and tourists.

3.4 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 τ_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, τ_z in (6), and its separate components, the elasticity η_z, in (5), and the zoomshock itself, ΔE_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

$$y_z = \alpha + \boldsymbol{\beta}\mathbf{X}_z + \varepsilon_z, \qquad z = 1, \ldots, 7201. \tag{10}$$

On the LHS of equation (10), we consider separately each of the three terms in equation (6): the zoomshock, ΔE_z; the elasticity, η_z ; and the total effect of the zoomshock on the employment in a neighbourhood, τ_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 residents, population density (residents per square kilometre), average broadband speed, percent of households covered by broadband, and a quadratic for retail and office space (in square kilometres 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 2, 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 for broadband speed, there are systematic differences in all these characteristics between positive and negative neighbourhoods.

A second reason why the analysis is best carried out by splitting the sample is illustrated by Figure 5. This provides binscatter plots of the relationship between the total effect on LPS employment, τ_z, and a selection of independent variables.[9] In each plot we control for neighbourhood characteristics and local authority fixed effects as in regression (10). This implies that the bins on the horizontal axes describe the conditional distribution of the named variable on each axis, and explains

[9] Diagrams for additional variables are in figure B.6 in the online appendix.

Table 2: 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	3.577	1,787	-114,490	1,730	-829.4	298.7	-24.51
Elasticity	0.246	0.228	-3.526	13.42	0.240	0.248	-1.20
Total effect	-1.109	118.2	-7,981	110.4	-40.95	13.01	-17.38
IMD	48.32	25.07	1.109	99.98	54.98	45.96	13.59
Housing quality	1.064	0.379	0.331	2.421	0.971	1.097	-12.47
Housing density	2.294	0.283	1.031	5.181	2.259	2.307	-6.24
Average age	41.34	4.943	23.93	62.40	39.82	41.87	-15.76
Population Density	42.79	40.03	0.0878	506.2	44.94	42.03	2.72
Broadband speed	60.98	21.37	16.92	543.7	61.16	60.92	0.43
Broadband coverage	0.758	0.0842	0.221	0.934	0.728	0.769	-18.51
Retail space	13.85	29.10	0	651	34.63	6.484	39.86
Office space	11.43	77.03	0	5,346	35.65	2.846	16.17

Note: Summary statistics for the variables used in the regression reported in Table 3. 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 value of a *t*-test of the difference in their means. They are all significantly different at the 1% level from each other, except the elasticity and the average broadband speed in the MSOA.

why there are negative values for some variables. The figures show the systematic differences in the relationship between τ_z and each variable between positive and negative neighbourhoods.

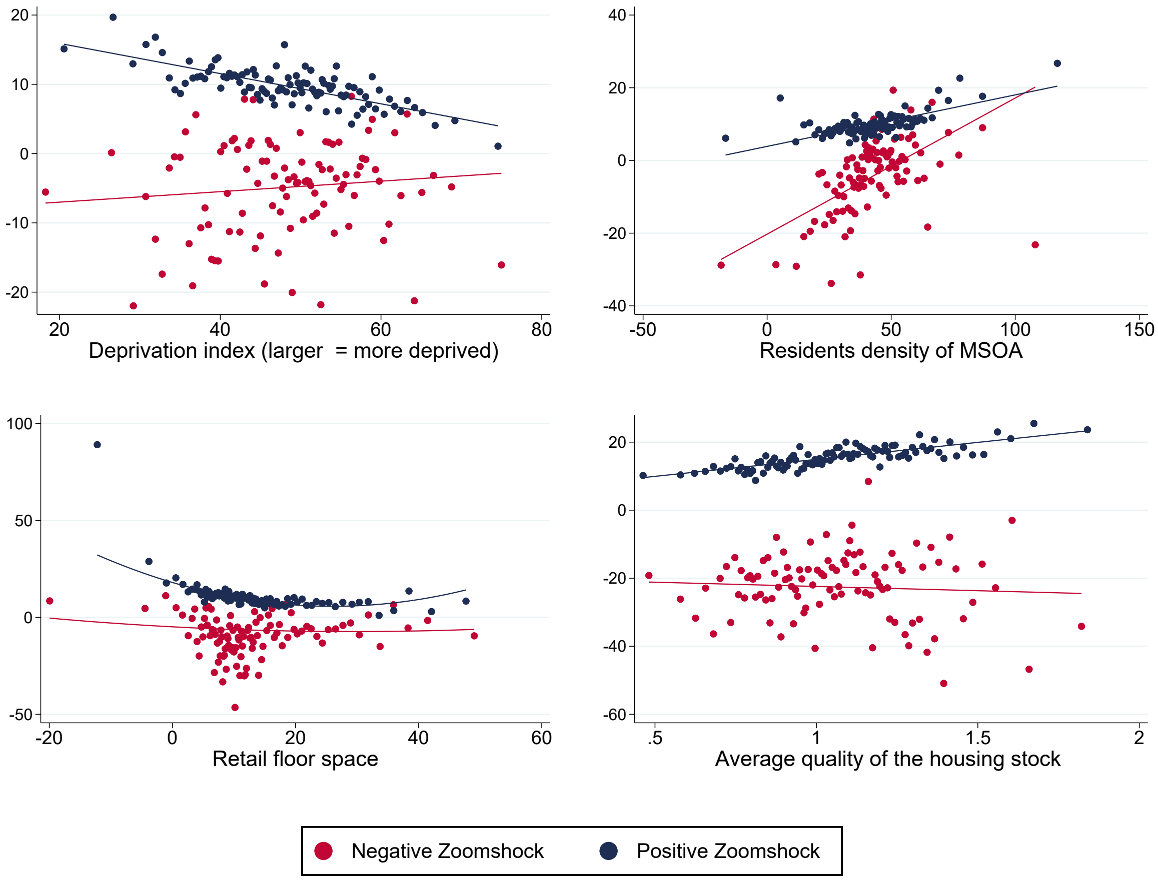
To confirm what Figure 5 suggests visually, we report in Table 3 our regression results for negative neighbourhoods in columns (1)–(3), and positive neighbourhoods in columns (4)–(6). In the regressions with elasticity as the dependent variable, we multiply η_z by 1000 to avoid leading zeros.

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. (2021), suggests that those living in more deprived areas are least likely to be in jobs where remote working is possible, potentially portending increased inequality.[11] The coefficients in the first three columns show

[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.

[11]The effect of the pandemic on distribution has been a concern since its outset (**?**), both in ad-

Figure 5:
Binscatter plots of τ, the LPS employment of the zoomshock.



Note: Each plot 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 (10).

no relationship between the IMD and the values of ΔE or τ, in neighbourhoods with a negative zoomshock. By contrast, Columns (4)-(6) and the pattern of blue dots in the north-west quadrant of Figure 5 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 similar implication of the south-east plot in Figure 5. 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

vanced (**?**) and in developing countries (**?**).

Table 3:
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	-2.393*	0.306	0.0144	-0.383**	-3.394***	-0.137***
	(1.260)	(0.903)	(0.0383)	(0.191)	(0.186)	(0.00929)
Housing quality	-218.0	-12.06	-2.061	32.10*	21.32	4.157***
	(138.5)	(71.98)	(3.087)	(18.76)	(15.05)	(0.756)
Housing density	73.62	-87.37**	-3.059*	5.646	-166.0***	-8.429***
	(65.02)	(37.59)	(1.669)	(14.43)	(13.59)	(0.733)
Mean Age	1.568	14.27***	0.624***	-0.677	-9.892***	-0.492***
	(2.710)	(3.565)	(0.159)	(0.955)	(0.905)	(0.0451)
Population Density	0.167	2.683***	0.103***	0.397**	1.593***	0.0723***
	(0.458)	(0.550)	(0.0249)	(0.184)	(0.128)	(0.00750)
Broadband speed	-0.132	0.201	0.00947	0.428***	0.0437	0.000972
	(0.819)	(0.640)	(0.0259)	(0.152)	(0.118)	(0.00552)
Broadband coverage	-297.5***	112.4	10.45	-33.92	510.5***	22.03***
	(110.7)	(172.7)	(7.432)	(42.75)	(46.80)	(2.542)
Retail floor space	-5,321***	-1,233	-41.77	-10,187***	-5,444***	-248.5***
	(1,161)	(873.1)	(33.01)	(533.1)	(504.5)	(26.00)
Office floor space	-1,243**	-13,702***	-531.0***	-614.9	-16,754***	-777.8***
	(631.6)	(1,003)	(43.54)	(725.0)	(557.5)	(30.41)
Retail space^2	26,228***	-21,470***	-867.0***	109,348***	48,013***	1,812***
	(7,584)	(7,555)	(267.0)	(12,833)	(12,785)	(695.7)
Office space^2	13,168**	32,228***	791.1**	18,935**	192,768***	10,274***
	(5,488)	(8,186)	(379.0)	(8,429)	(8,141)	(591.4)
Observations	1,738	1,738	1,738	5,317	5,317	5,317
R-squared	0.237	0.611	0.632	0.317	0.566	0.663

Note: OLS estimates of the association between neighbourhood characteristics and the elasticity η_z defined in expression (5), the zoomshock ΔE_z, (2), and the total effect on LPS employment τ_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.

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 τ_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. The table suggests that, in areas with more residents per household, areas for example with a low proportion of singles or pensioners, 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 τ_z is lower. And so lower-income neighbourhoods will see larger declines or lower growth in LPS spending. Figure B.6 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 3 shows that the zoomshock is higher in more densely populated neighbourhoods. An increase in density is also associated with an increase in the magnitude of τ, the total effect of the zoomshock. 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 5 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]

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

The final set of covariates, broadband speed and coverage, capture connectivity. Slow internet connections are an important barrier to remote work as shown for the US by Barrero et al. (2021a). Of course, 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 zoom-shocks. Together with the lack of effect on the zoomshocks or τ_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 ΔE_z and τ_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 zoomshock neighbourhoods, as might be expected given that broadband coverage varies little in them, see Table 2. Among positive neighbourhoods the impact is greater in areas with more and faster broadband. Taking all these results together, the interpretation for positive zoomshock 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 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 2, 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 3 also suggest that the elasticity as well as the zoomshock is lower in negative zoomshock neighbourhoods with more retail space. The results for office space are as would be expected. The coefficient on ΔE_z and τ_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 5 and Figure B.6. 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 3.

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; **?**). 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. This, it seems plausible, will also 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 demand has increased the most are those with relatively few suppliers due to low amounts of retail space. It follows that 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, our analysis provides first estimates reflecting how LPS business and workers are affected by where other workers spend their day. Metrics such as the LPS spending elasticity will form the bases, once refined and measure precisely local employment multipliers, a necessary tool to assess the implications of place-based policies for city design and urban planning. Second, the short-term implications for the provision of LPS around the workplace will likely continue the adjustment to lower demand for services when work is done remotely some of the time: this might mean a shift of LPS supply from city centres to residential areas. For this demand to be realized as a market transaction, thereby avoiding LPS job losses, it is imperative that workers and businesses are able to move to where demand is: over time, the transition to more remote working may more permanently alter demand for transport and relocate some types of spending to the locality of workers' homes rather than their workplaces while attracting other types. For example, commercial space in cities may be turned over to provision of other services such as entertainment, retailing, hospitality during leisure time in place of lost business connected with workplaces and more inward commuting to cities may occur during the evenings and weekends rather than in the mornings. Urban planners may need to reimagine the use of commercial space and infrastructure to accommodate these changes.

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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 Work From Home Survey

A.1.1 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 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.1.2 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

$$WFH^{2019}_{i,o,z} = \frac{\frac{Q9_{i,o,z}}{8} - Q57}{5} \tag{A1}$$

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

$$WFH^{2019}_{o,z} = \frac{1}{n_{o,z}} \Sigma_i WFH^{2019}_{i,o,z} \tag{A2}$$

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

A.2 Data sources

A.2.1 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.2.2 Neighbourhood retail and hospitality output

For Equation (5), we calculate the total spending on retail and hospitality for each MSOA ($S^{2019}_z + \Omega^{2019}_z$) as the total number of workers in the area z 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 LPS 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 LPS expenditure.

A.2.3 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.

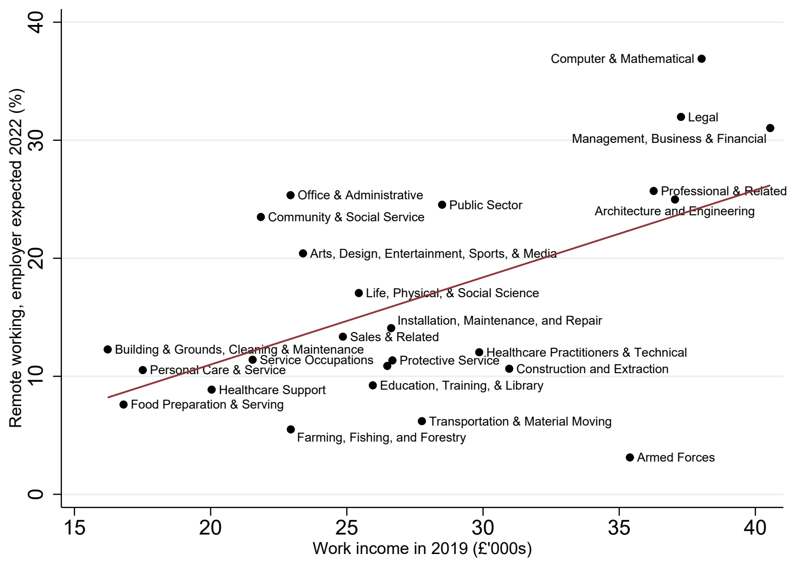
Figure B.6 shows the binscatter plots between RHS variables and the total effect of the zoomshock for the variables included in the regressions, but not plotted in figure 5, namely the average age and the average number of residents in a dwelling in the MSOA, the total floor space within its boundary, and the percentage of dwelling with broadband.

The next diagram, Figure B.3, shows binscatter plots linking the change in weekday retail activity and the percent change in LPS spending for 295 cities in England and Wales (left) and 33 cities making up the Greater London area (right). Retail activity is measured from the COVID-19 Community Mobility Reports retail index (Google, 2022), averaged over all weekdays over the period from June 2021 to December 2022. The retail index reflects the percent change in footfall in retail and hospitality establishments, relative to the median footfall for the five-week period from 3 January to 6 February, 2020. These figures show a clear positive correlation between our estimated percent change in LPS spending, computed as $\Delta S_z/(S_z + \Omega_z)$ from (4), and retail footfall. A percentage point increase in the estimated spending shock is associated with an increase in retail footfall of 1.6 percentage points for London and 5.1 percentage points for other cities in England and Wales.

In Figure B.4, we present the Office for National Statistics (2024) Pret A Manger index of the average weekly till transactions in the first four weeks of 2020 (between Friday 3 January and Thursday 30 January 2020). This only includes in store transactions, and do not include online or delivery sales, and hence fits well our idea. The figure, shows the persistent gap between the transactions taking place in London suburban locations and the equivalent in for City workers. The dips in the indices correspond to public holidays. The difference in the index is steady at between 30-40. This demonstrates, subject to caveats about use of data that is seasonally unadjusted, from a single retail outlet, that there appears to be a persistent gap that has emerged between suburban and City locational transactions, as our analysis suggests.

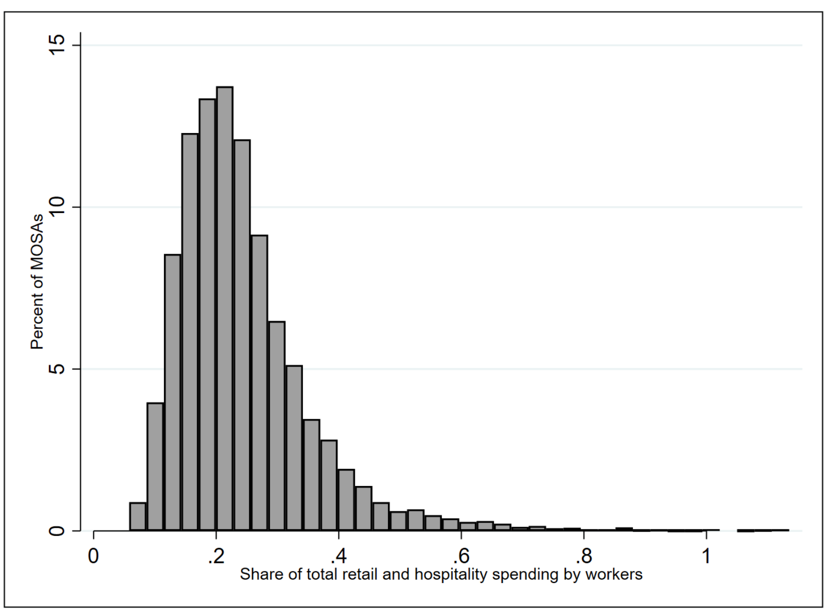
Finally, Table B.3 reports the output for the same regressions in Table 3, but expanding the sample to include *all* MSOAs, even those that, for the huge size of the zoom-shock, can be considered extreme outliers. By and large the results are confirmed.

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



Note: 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



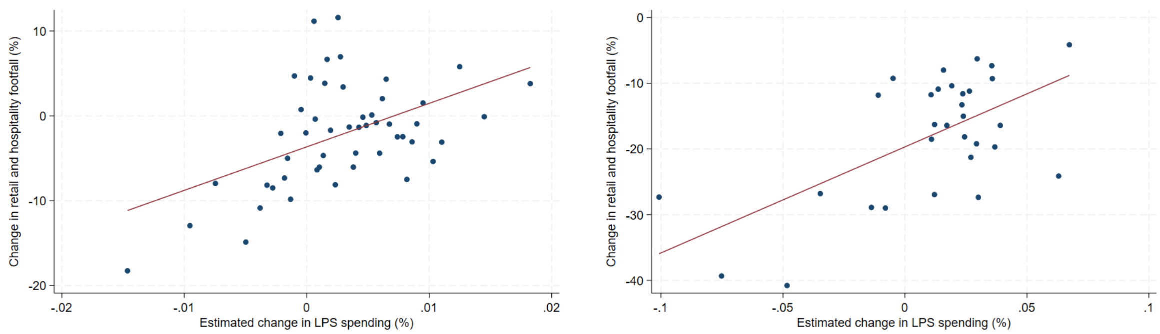
Note: This histogram shows the distribution of neighbourhoods according to the share of total spending that is attributable to workers working in the MSOA.

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	

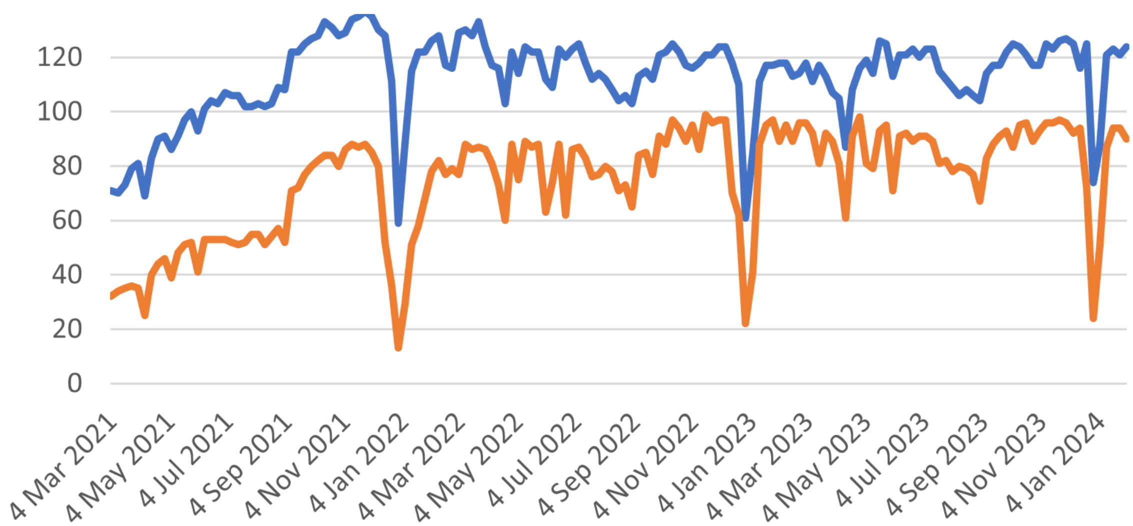
Notes: This table reports working from home rates by occupation and location of job (in 2019). *Smaller LAs* refers to all local authorities outside the Greater London area which are not in the top 15 cities by population size. The *Large LAs* are the top 15 largest local authorities by 2019 population 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:
Binscatter plots of τ, the LPS employment of the zoomshock.



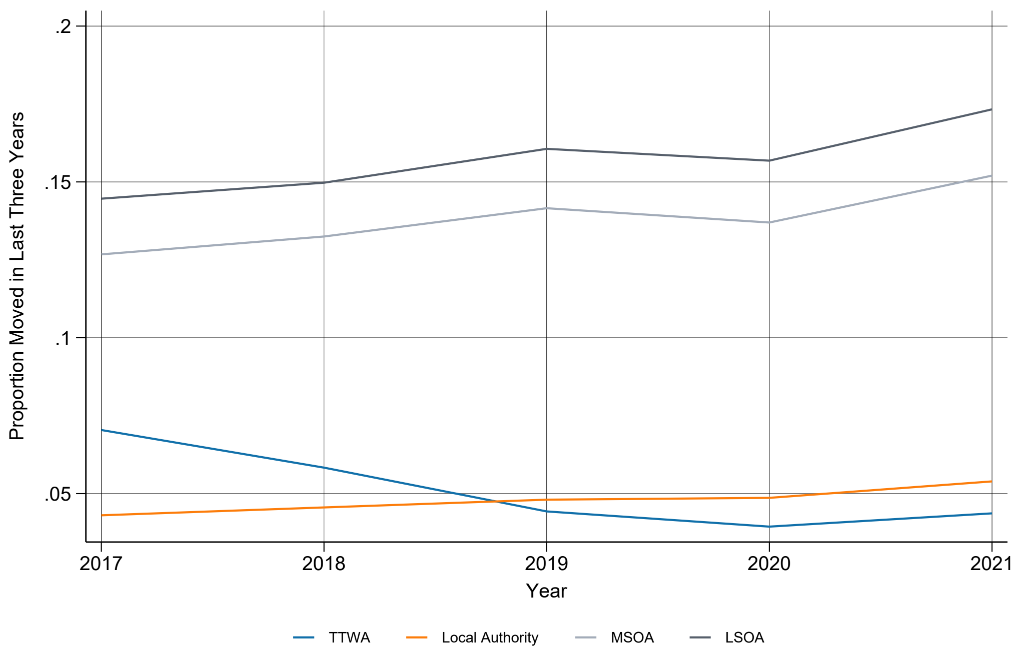
Note: These binscatter plots describe the relationship between the estimated spending shock and the percent change in footfall in retail and hospitality establishments at the local authority level over the period June 2021 to December 2022 relative to January-February 2020. The RHS panel are London boroughs, and the LHS the remaining local authorities in England and Wales. The red line is the line of best fit in each panel.

Figure B.4:
The ONS Pret A Manger Index.
London suburban (blue) and City stores (orange)



Note: Weekly data showing transactions from approximately 400 Pret A Manger stores around the UK. The vertical axis measures the ratio (multiplied by 100) of the weekly till transactions and the weekly average in the period from Friday 3 January to Thursday 30 January 2020. Data is not seasonally adjusted. The blue line reports this ratio for "London Suburban neighbourhoods", the red one for London City Workers.
Source: Pret A Manger and Office for National Statistics (2024).

Figure B.5:
Movers in England and Wales.



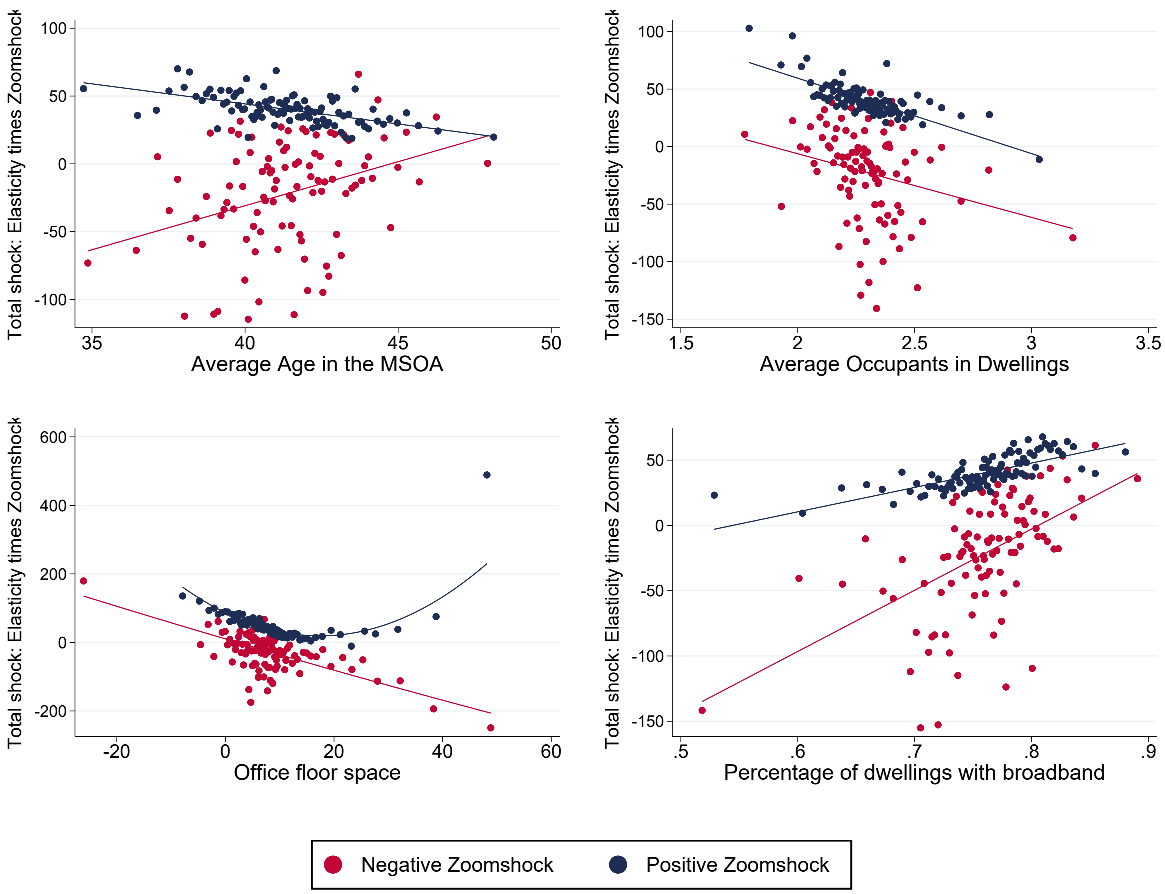
Note: Each line reports the percentage of workers who have not changed job relative to three years previously, but who have changed the area in which they live. The blue line reports the percentage who have changed Travel to Work Area, the orange line the percentage who have changed Local Authority, with the light and dark grey lines recording the percentage changing MSOA and LSOA, respectively. We exclude workers who have changed job in the previous three years, and those not in full time employment. Data are from the Annual Survey of Work and Employment (Office for National Statistics, 2022).

Table B.2:
Propensity to move and remote working potential: Robustness tests

	(1) Col. (1) in Tab. 1	(2) Change LSOA	(3) Change LA	(4) Work fix. eff.
RemoteWork $\times$ PostCovid	0.003	0.004	-0.002	0.004
	-0.007	-0.006	-0.003	-0.006
Observations	227,608	227,608	227,608	227,605
R^2	0.16	0.17	0.16	0.16
Fixed Effects	TTWA	TTWA	TTWA	Work TTWA

Note: The same specification as Table 1, with different residential locations. In detail, Column (1) is the same as in Table 1, Column (2) has a change in the LSOA (a census level intermediate between the Output Area and the MSOA), the LA (column (3)) is a higher administrative divisions (there are around 300 in England and Wales). All regressions also include the same controls and fixed effects as in Table 1; robust standard errors are reported in parentheses. ***denotes $p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure B.6:
Bin scatter plots of τ, 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 (10) and the local authority fixed effects.

Table B.3: 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	-2.185*	1.227	0.0632	-0.383**	-3.394***	-0.137***
	(1.131)	(1.469)	(0.0885)	(0.191)	(0.186)	(0.00929)
Housing quality	-185.6	97.71	4.572	32.10*	21.32	4.157***
	(116.7)	(127.1)	(7.622)	(18.76)	(15.05)	(0.756)
Housing density	86.11	-287.1***	-14.02***	5.646	-166.0***	-8.429***
	(56.37)	(76.64)	(4.138)	(14.43)	(13.59)	(0.733)
Mean Age	1.620	15.23**	0.607*	-0.677	-9.892***	-0.492***
	(2.429)	(6.785)	(0.364)	(0.955)	(0.905)	(0.0451)
Population Density	-0.221	5.959***	0.326***	0.397**	1.593***	0.0723***
	(0.385)	(1.237)	(0.0792)	(0.184)	(0.128)	(0.00750)
Broadband speed	-0.138	0.967	0.00293	0.428***	0.0437	0.000972
	(0.796)	(1.177)	(0.0741)	(0.152)	(0.118)	(0.00552)
Broadband coverage	-361.7***	607.5**	35.20**	-33.92	510.5***	22.03***
	(100.6)	(290.8)	(16.19)	(42.75)	(46.80)	(2.542)
Retail floor space	-2,455***	-4,891***	-237.4***	-10,187***	-5,444***	-248.5***
	(416.6)	(692.2)	(43.46)	(533.1)	(504.5)	(26.00)
Office floor space	557.2***	-16,805***	-821.5***	-614.9	-16,754***	-777.8***
	(192.7)	(1,286)	(84.69)	(725.0)	(557.5)	(30.41)
Retail space^2	3,961***	2,561	663.4***	109,348***	48,013***	1,812***
	(1,475)	(3,807)	(235.4)	(12,833)	(12,785)	(695.7)
Office space^2	-195.8	-6,230***	-690.5***	18,935**	192,768***	10,274***
	(148.2)	(847.3)	(58.17)	(8,429)	(8,141)	(591.4)
Observations	1,884	1,884	1,884	5,317	5,317	5,317
R-squared	0.236	0.981	0.985	0.317	0.566	0.663

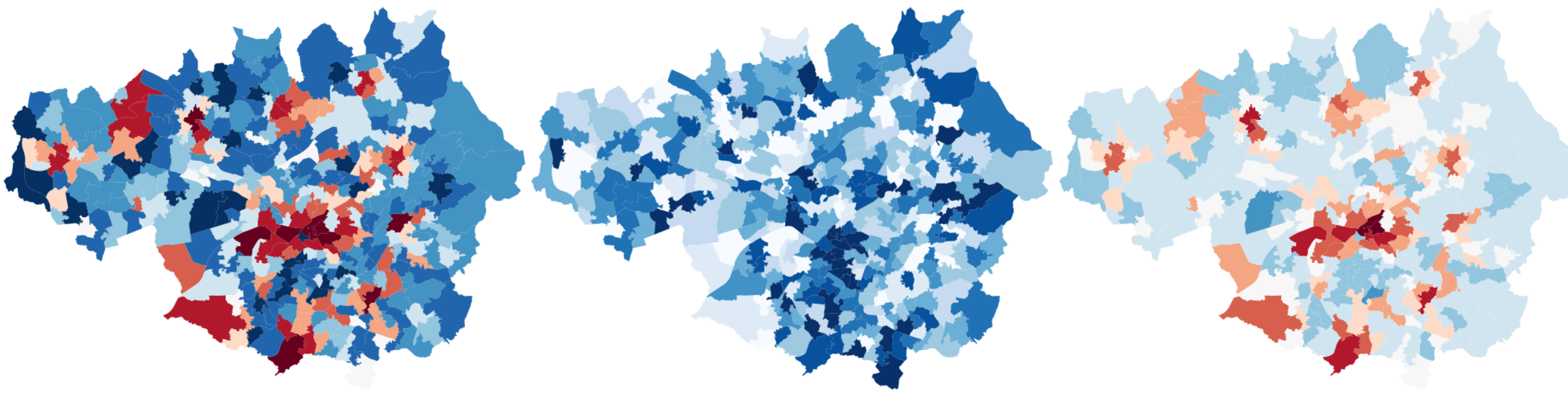
Note: This table corresponds to columns (1)-(3) of Table 3, but including also the 45 MSOAs that have experienced a negative zoomshock exceeding 5000 or a total impact exceeding 2000 in absolute value.

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 2 in the text.

(a) Zoomshock (ΔE_z) **(b)** LPS elasticity (η_z) **(c)** Total effect (τ_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, τ_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.

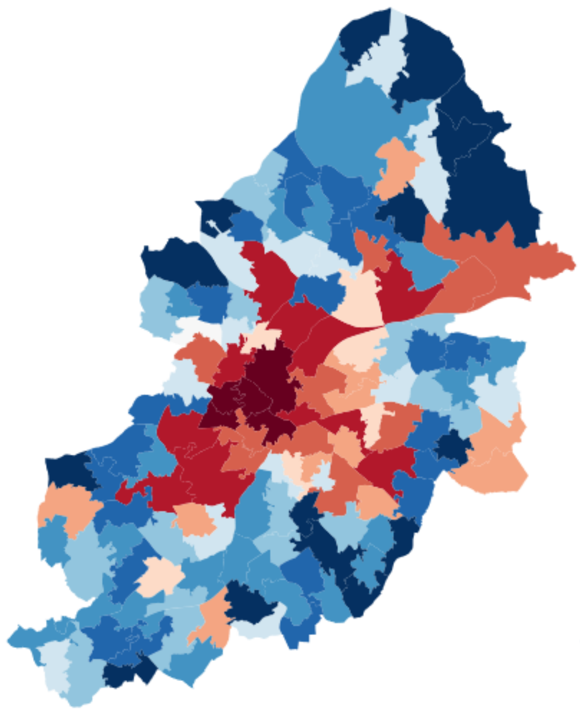
Figure C.2: Remote working and LPS workers: Greater London

(a) Zoomshock (ΔE_z) **(b)** LPS elasticity (η_z) **(c)** Total effect (τ_z)

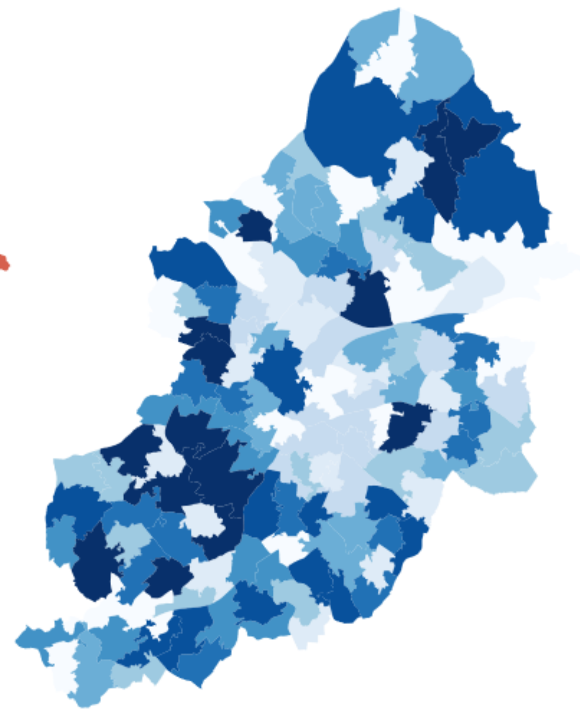
Note: In the choropleth maps, each MSOA in the Greater London is coloured according to the quantile in which the corresponding variable falls in the ranking of the MSOAs. Other details as for figure C.1.

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

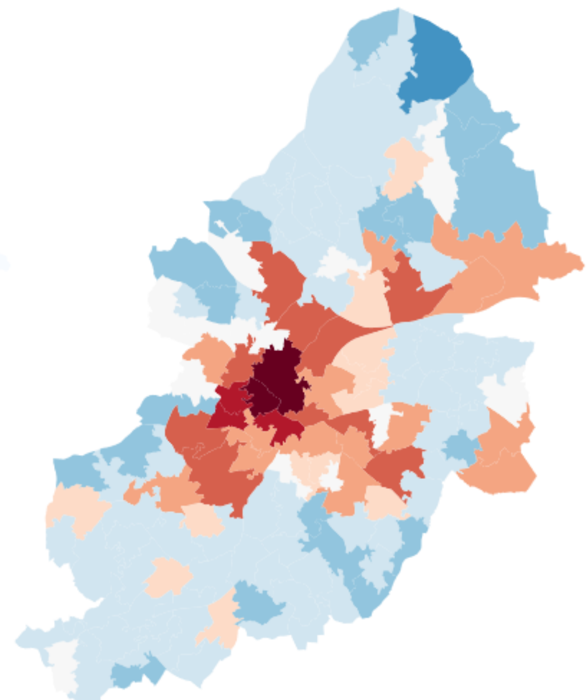
(a) Zoomshock (ΔE_z)



(b) LPS elasticity (η_z)



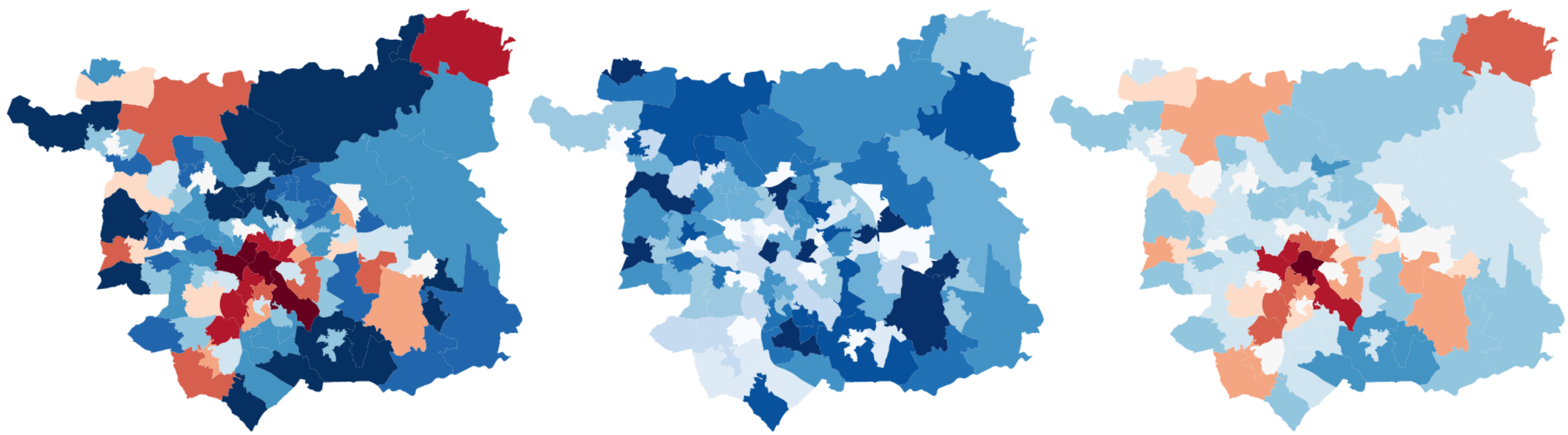
(c) Total effect (τ_z)



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 (ΔE_z) **(b)** LPS elasticity (η_z) **(c)** Total effect (τ_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.