Urban density and viral infection: Disentangling the role of residential and employment neighborhood structures

Carlo Corradini[*], Jesse Matheson[†] and Enrico Vanino[‡]

April 2022 Version

Abstract

In this paper we study the relationship between the spatial distribution of population, local labour force, and viral spread. We study the spread of COVID-19 in the first year of the pandemic across 6,700 neighbourhoods in England. Our unique data set allows us to explicitly distinguish between where workers live and where they work, as well as whether workers worked remotely or onsite during the pandemic, documenting three important results. First, the neighbourhood density of both residents and workers is important. Second, over and above density, the type of work done by residents and workers has a critical role on viral spread. A greater concentration of remote work is associated with fewer cases, while a greater concentration of onsite work is associated with more cases. Third, our results are influenced by the level of neighborhood deprivation, with higher contagion in high-deprivation neighborhoods with large shares of keyworkers, and lower infection rates in affluent areas where residents can work from home. We speculate on the reasons for this looking at within-household house crowding and at the skill intensity of local occupations. Our results can rationalise spatial variation in lockdown effectiveness as being driven by the distribution of workers within urban settings. These findings have important implications for the social justice of public health measures, and provide useful insights for designing future economic policies and public health strategies for the endemic phase of the infection, targeting more precisely the neighborhoods more vulnerable from an economic as well as a contagion perspective.

Keywords: COVID-19, Residential Density, Employment Structure, Urban Density, Public Health Restrictions.

JEL Classification: H12, I12, R10, R12.

1 Introduction

A striking feature in outbreaks of infectious diseases is the considerable spatial heterogeneity observed for both morbidity and mortality. Research has shown how such variation broadly reflects differences in the socio-economic structure across locations, including income and age distribution, quality of healthcare and institutions (Carozzi et al., 2020; Desmet and Wacziarg, 2021; Rodríguez-Pose and Burlina, 2021; McCann et al., 2021). Population density has received particular attention

[*]University of Birmingham, Birmingham, UK.
[†]University of Sheffield, Sheffield, UK.
[‡]University of Sheffield, Sheffield, UK. Corresponding author: e.vanino@sheffield.ac.uk
Acknowledgments: This work has been supported by the Regional Studies Association (RSA) Small Grant Scheme on Pandemics, Cities, Regions & Industry. We are grateful for the feedback received at the RSA 2021, the UEA 2021 North America and the UEA 2022 European conferences. We would like to thank Rhiannon Thomas and Yusuf Sohoye for their research assistance.

in previous analysis, reflecting the role of physical proximity as key channel for viral contagion. However, population density remains a black box. In particular, we know little about the underlying mechanisms through which economic activity and population density interact in viral spread.

In this paper we contribute to the unpacking of the urban density black box by looking at the role of local labour markets in viral spread. Specifically, we ask how much of the variation in viral spread observed within an urban area can be explained by the distribution of the labour force. We explicitly examine two important margins not previously studied. First, we distinguish between the concentration of people who live in a neighbourhood, the *residents*, and the concentration of people who work in a neighbourhood, the *workers*. Second, we decompose our populations of residents and workers according to the nature of their work, distinguishing between jobs that can be done from home, *homeworkers*, jobs that need to continue onsite, *keyworkers*, and non-essential onsite jobs that likely experienced a pause during periods of public health restrictions.

We use data reflecting the spread of COVID-19 cases in the first year of the pandemic merged with detailed information on population and labour market composition of neighborhoods across England. These data have a number of benefits. First, we have granular geographic information on employment structure and residential population distribution by occupation.[1] A neighbourhood reflects approximately 7,000 residents (3,000 residential buildings), allowing us to exploit within-city variation in COVID-19 cases, residents and employment. A second benefit is that we can rely on a list of jobs designated as *keyworkers* published in the early stages of the pandemic by the UK Government.[2] Over the lockdown periods that we examine, only keyworker jobs were allowed to continue working onsite. Combining this with information reflecting occupations that can be done from home, following Dingel and Neiman (2020) and De Fraja et al. (2021), we decompose workers and residents populations for each neighbourhood according to these important margins of employment. Using granular neighbourhood data, our estimation strategy allows us to control for unobserved variation in policy or social norms at the local labour market level. Our identification exploits variation in the occupational structure of residents and workers which existed before the COVID-19 pandemic.

We document four important results. First, the neighbourhood density of both residents and workers is important. A one percent increase in the density of people who work in a neighbour-

[1] Occupation is specified according to the UK Standard Occupational Classification: at the four-digit code for residents, and the three-digit code for workers.

[2] In the UK, this group included not only medical personnel and first responders, but more broadly jobs in the energy sector, in primary education and child care, agriculture and food production, critical retail, some manufacturing jobs, as well as public transport workers. A summary of this list is available in Table A1 in the Appendix.

hood is associated with a statistically significant increase of 0.016 percent in weekly cases; this is almost twice the magnitude of the corresponding elasticity for residential population density. This is particularly interesting, considering that a recorded COVID-19 case corresponds to the infected person's neighborhood of residence. Second, over and above density, the type of work done by residents and workers has a critical role on viral spread. A greater number of jobs that can be done from home, both for residents and workers, is associated with fewer cases, while a greater number of key worker jobs is associated with more cases. Back of the envelop calculations suggest that 47 more residents able to work from home reduced infection in a neighborhood by 1 case per week (almost one-third relative to the mean), while 47 more resident keyworkers in a neighborhood increases cases by 2 per week. Similar results are found for the occupation composition of people working in a neighborhood, although smaller in magnitude. Third, we observe heterogeneity in the importance of occupational composition of residents, but not workers, according to neighbourhood deprivation. In more deprived neighborhoods key worker jobs have a stronger positive association, while jobs done from home have a weaker negative association, with viral spread, than in low-deprivation neighbourhoods. We speculate on the mechanisms driving this by looking at within-household house crowding and at detailed skill intensity differences of occupations across the neighbourhood deprivation distribution. Fourth, we find that these relationships are particularly important during lockdown periods, with important policy implications for the social justice of public health policies, shifting the social and economic burden of viral infections from affluent neighborhoods characterised by a large share of high-skilled residents able to work from home to the most deprived areas within cities where most low-skilled keyworkers live. These results are shown to be robust to different measures of density and virus spread.

This study contributes to the literature on the public health and economic implications of viral infections within urban centres, which has expanded considerably since the COVID-19 pandemic. A number of previous studies look at the relationship between population density and viral spread. The 1918 influenza pandemic is found to have had a higher mortality rates in dense, urbanised, areas (Garrett, 2007; Chowell et al., 2008). Evidence for the recent COVID-19 pandemic is less clear: some studies find a positive effect (Wong and Li, 2020; Allcott et al., 2020; Desmet and Wacziarg, 2021; Almagro and Orane-Hutchinson, 2020), while other studies find mixed or not significant evidence once other factors are controlled for (Carozzi et al., 2020; Ascani et al., 2021; Armillei and Filippucci, 2020; McCann et al., 2021).

A smaller set of studies has provided evidence pointing to a critical role of industrial density and specific employment classes in viral spread, for example exploring the link between the density of workers in essential sectors during the COVID-19 pandemic (Almagro and Orane-Hutchinson, 2020; Ascani et al., 2021; Di Porto et al., 2022). However, the differential impact of local labour forces on viral transmission with respect to where people live and where they work has so far received limited attention. In particular, one channel through which local labour markets may be important is the use of lockdowns as public health measures. While the literature broadly indicates that stay-at-home orders have led to a reduction in COVID-19 cases (Alvarez et al., 2020; Acemoglu et al., 2020; Glaeser et al., 2020; Bourdin et al., 2021), we know little about how spatial variation in the types of jobs done may lead to spatial variation in the prevalence of cases and the effectiveness of these public heath restrictions. For example, will workers continuing their jobs onsite affect viral spread in neighbourhoods where these workers work, or only in neighbourhoods where these workers live?

The important insights from previous research are limited by the broad level of spatial aggregation, considering data at provincial or regional level, or occupational aggregates that do not distinguish between residential and workplace locations. A number of papers highlight the importance of using a granular level of spatial analysis in studying the spread of COVID-19 infections (Glaeser et al., 2020; Guha et al., 2020; Kuebart and Stabler, 2020; Chang et al., 2021). The level of data aggregation limits the ability to explain considerable variation in contagion within the same urban areas (Thomas et al., 2020), or similarly high incidence of COVID-19 cases observed in both large urban agglomerations as well as small cities in rural environments (Kuebart and Stabler, 2020; Bailey et al., 2020). A finer level of spatial granularity is therefore necessary as COVID-19 becomes endemic in the society, in order to effectively design targeted public health measures addressing highly localised outbreaks linked to different types of social and economic interactions.

By bringing together separate literature looking at population density and local occupational structures, we are able to disentangle the roles that residential and employment locations, across different types of jobs, play in population viral spread. This allows us to unpack the channels through which urban density and viral spread are related, understanding how viral diseases spread across neighbourhoods through social and economic interactions. This is increasingly important as governments aim to reopen economies, removing public health restrictions and transitioning to an endemic phase of the health emergency, adjusting to live with the virus. In particular, a more nuanced comprehension of where and how contagion takes place, whether at home or at the workplace, and in the latter case through which type of jobs, will be increasingly important as outbreaks slowly recede and viral diseases become endemic, with consequences for the everyday functioning of the economy in terms of self-isolation, absenteeism and labour productivity. This is also critical for designing policies addressing the economic effects of the health crisis, as discussed in recent papers exploring the impact of the COVID-19 pandemic on productivity (McCann and Vorley, 2021), jobs and income loss inequalities (Adams-Prassl et al., 2020), SMEs performance (Bartik et al., 2020a), and the shift toward working from home (Bartik et al., 2020b; De Fraja et al., 2021).

The structure of the paper is as follows. In Section 2, we review the emerging literature on the links between density, employment structure and COVID-19 together with an overview of the main policy interventions adopted in England to hamper transmission. Section 3 outlines the data used. Section 4 discusses the research design for the empirical analysis. Results are presented in Section 5. Section 6 concludes the paper discussing policy implications.

2 Literature Review

A growing literature has rapidly emerged on the spatial variation of incidence rates of viral infections following the outbreak of the COVID-19 pandemic. In particular, significant attention has been dedicated to the role of population density. Densely populated areas are naturally defined by important differences in terms of socioeconomic elements that have clear implications in the context of the pandemic, such as age distribution, income, ethnicity and health infrastructure (Almagro and Orane-Hutchinson, 2020; Sá, 2020; Desmet and Wacziarg, 2021). Another element potentially connected to density is pollution. Studies based on US county and UK regional data indicate a significant effect of air pollution whilst controlling for several factors, including population size and density (Wu et al., 2020; Travaglio et al., 2021). Similar effects have been found using data from other countries (Cole et al., 2020; Fattorini and Regoli, 2020). Once these elements are controlled for, density potentially retains a critical role in the diffusion of COVID-19 considering the transmission mechanisms of the SARS-CoV-2 virus. The link between airborne transmission of COVID-19 and population density reflects insights from spatial variation patterns of the 1918-1919 influenza pandemic. Exploiting US city-level data, previous research suggests a positive correlation between population density and influenza mortality (Garrett, 2007). Exploring the economic consequences of the 1918 pandemic at State and city level, Correia et al. (2020) suggest that higher mortality in urbanised areas with greater manufacturing activity could be linked to higher density. Looking at both 305 administrative units and 62 counties in the UK, Chowell et al. (2008) find a markedly higher mortality in urban areas, but no clear association between death rates and measures of population density.

Contributions on the presence of a link between population density and COVID-19 have similarly provided mixed findings, with differences in the evidence seemingly defined by the level of spatial aggregation adopted. Using data at the provincial level in Italy, Ascani et al. (2021) find no evidence of an effect of population density on COVID-19 cases. Similarly, Rodríguez-Pose and Burlina (2021) explore excess mortality in the first wave of the pandemic across European regions but find no effect of density once institutional factors are controlled for. Carozzi et al. (2020) explore US county data and find that density affects the timing of the outbreak, but find no evidence that population density is positively associated with time-adjusted COVID-19 cases and deaths. They suggest this may be due to differences in social distancing measures, access to healthcare and demographics in urbanised areas. Conversely, Wong and Li (2020) show that population density is an effective predictor of cumulative infection cases in the US at the county level; also, they note higher spatial resolution would be preferable, as COVID-19 transmission is more effectively defined at sub-county geographical scales. In line with this, Desmet and Wacziarg (2021) look at the role of density at county level data on COVID-19 reported cases and deaths in the US finding limited evidence on the role of population density on the former, but a positive effect on the latter. However, they show effective density - calculated as the "average density that a random individual of a county experiences in the square kilometer around her" - is a strong predictor of cases and death. Similarly, a proxy measure for persons per household is also found to exert a significant effect on both.

The role of density is also underlined by studies exploring cross-sectional data at higher levels of spatial aggregation. In the US context, researchers have found robust evidence on the link between density defined as the number of people per household and COVID-19 cases looking at the ZIP level for selected cities (Almagro and Orane-Hutchinson, 2020; Guha et al., 2020). Similar results have been found analysing MSOAs in England and Wales (Sá, 2020). Conversely, focusing on Italian municipalities, Armillei and Filippucci (2020) find a negative correlation between population density, as well as measures of house crowding, and excess mortality. Overall, these findings suggest that it is not density per se, but the likelihood of closed contacts - as also underlined by the consistent effect of house crowding proxies - that matters. Thus, COVID-19 cases, and subsequently death rates, result from highly localised interaction, which is not simply a function of being in a large urban area as opposed to smaller city environment, but also the type of social interactions occurring.

In this regard, the role of density and its localised nature are inherently connected to the structure of the local economy. Ascani et al. (2021) explore a spatial autoregressive model of COVID-19 cases in the Provinces (NUTS2) of Italy to look at the role of the underlying economic structure, defined as an employment-weighted Herfindahl–Hirschman index. They find evidence suggesting larger employment in geographically concentrated industries positively impacts COVID-19 cases. This effects seems to be driven by manufacturing employment. Thus, they suggest activities that are usually defined by industrial agglomeration advantages may be more conducive to COVID-9 transmission. Interestingly, the coefficient for population density is negative once the economic structure is controlled for. Armillei and Filippucci (2020) highlight similar elements, with the share of industrial and trade employment being positively associated with excess mortality, whilst service employment share is found to have a negative relationship. Almagro and Orane-Hutchinson (2020) offer a more disaggregated view on the role of occupations, looking at COVID-19 cases in New York across 13 different employment classes. Their findings suggest that the share of employment in specific sectors is positively associated with positive tests for COVID-19, notable Essential Professional, Industry and Construction and Transportation. However, only the latter remains significant after the introduction of stay-at-home orders in New York. Interestingly, the role of public transport - which has received contrasting results in other studies (Sá, 2020; Armillei and Filippucci, 2020; Desmet and Wacziarg, 2021) - is no longer significant once occupation variables are controlled for (Almagro and Orane-Hutchinson, 2020).

While most of these contributions explore density using a cross-section perspective, the COVID-19 pandemic has been characterised by strong policy intervention aimed at restricting mobility, including stay-at-home orders in the US and similarly public health measures in the UK (Alvarez et al., 2020; Acemoglu et al., 2020; Courtemanche et al., 2020). In the period between March 2020 to April 2021, England has gone through three different lockdown phases. At the end of March 2020, lockdown measures were introduced to reduce transmission during the first wave of the COVID-19 crisis, with only essential workers allowed to go to work. These measures were slowly relaxed in May, with schools and non-essential shops reopening in June. A second, less severe, lockdown was initiated in the autumn, with work-from-home recommendations wherever possible. These measures were increased in November to the level of the first lockdown. Measures were removed in early December, but they returned in full at the end of December, with a third national lockdown officially introduced on the 6th of January at the onset of the third wave. This final lockdown measures would be relaxed only starting from March 2021.

As shown by Glaeser et al. (2020) exploring zip-code level data for selected cities in the US, restrictions on mobility may lead to significant reduction in COVID-19 cases, with total cases per capita decreasing up to 30% for every ten percentage point fall in mobility. Similarly, the lockdown strategy introduced in Italy at the beginning of the first wave has been shown to reduce the spread of the virus away from provinces first hit (Bourdin et al., 2021). After the onset of the pandemic, the role of density has not been shaped solely by policy. Indeed, changes in mobility reducing transmission rates have also been the result of voluntary social distancing responses (Allcott et al., 2020). Paez et al. (2020) present similar results by looking at COVID-19 cases across Spanish provinces, and identifying a significant but negative effect of density during a lockdown phase when only essential activities were allowed, suggesting the presence of a stronger behavioural response in places with a higher perceived level of risk.

These changes in behaviour and mobility have effects across all channels of COVID-19 transmission. Evidence from New York across the first wave of cases suggests the positive effect of the share of employment in essential and non-essential professional and service occupations reduces and then disappears after the introduction of stay-at-home orders (Almagro and Orane-Hutchinson, 2020). Only workers in transportation and other health sectors remain a positive factor in the number of cases, pointing to lockdowns reducing risk in public places or the workplace, but only mitigating the transmission in occupations still operating through these mobility restrictions. Interestingly, the results by Almagro and Orane-Hutchinson (2020) also highlight that while lockdowns may reduce transmission across occupational categories, the effect of household size remains unchanged, suggesting that shelter-in-place policies may have a limited effect on intra-household contagion.

These insights suggest that the relationship between density and COVID-19 incidence may be strongly localised. In particular, we would expect density to drive transmission mostly in specific settings, where contact is more persistent and sustained. This suggests it is density where people live that may lead to higher COVID-19 incidence, given also the way in which cases and deaths are reported. In the same way, household size and households in poorer areas may suffer from higher incidence to COVID-19, due to the higher density in the places where people spend more of their time indoor, at home, leading to high levels of intra-household contagion.

Nonetheless, it is the nature of the social and economic interactions that could help us to understand how viral diseases spread across neighbourhoods. This is likely reflected in the occupational structures of residents and workers in a neighborhood. As most workers moved to a work-from-home solutions during the pandemic, key workers still operating onsite and engaging in their usual activities can be expected to achieve much lower social distancing, even with the introduction of public health recommendations in their workplace. Thus, for the same level of density, we would expect areas with a higher share of key workers living and working there to be characterised by higher levels of COVID-19 incidence. Again, also in this case very similar dynamics should be expected in respect to the role of household density and deprivation. These are likely to be exacerbated in places with more key workers, as they would not have the possibility to work from home without losing income, and would be more exposed to contagion during their work, before spreading contagion once back home.

Finally, previous evidence suggest these effects to be significantly affected by lockdown policies. In the absence of lockdowns, the link between key workers density and COVID-19 in more deprived areas can be expected to be much more defined. However, lockdowns are likely to reduce the transmission through key workers as these enter in contact with a much smaller part of the population. Thus, the link between key workers and deprived areas should recede. We would therefore expect a similar reduction on COVID-19 cases in deprived areas with a higher share of resident key workers. However, this may not be the case in areas with higher population density. Reflecting previous findings (Almagro and Orane-Hutchinson, 2020), lockdowns can be expected to mitigate contagion in places with larger and less deprived households, but their effect may not be as useful in more deprived areas where contacts and social distancing are more likely to remain elevated.

3 Data

Our analysis is based on several datasets linked together at the neighbourhood level. A neighbourhood is defined by the Middle Super Output Area (MSOA), a geographic hierarchy defined by the UK Office for National Statistics. There are 6,791 MSOAs in England, with a mean area of 19 km^2 and an average population of 7000 people (3000 households ca). Towns and cities are defined by Local Authorities Districts (LAD), the geographic area governed by a single municipal council. Each local authorities district is made up of MSOAs, and all MSOAs are unique to a local authority district. Importantly, all public health measures in the UK during the pandemic are either administered at the national level or the LAD level. For simplicity we will refer to these geographic units simply as neighbourhoods and cities. Our analysis focuses on the period between March 2020 and April 2021. This reflects the period starting from the beginning of the first nationwide lockdown (26 March 2020), to the reopening of non-essential businesses (12 April 2021).

3.1 COVID-19 Data

Data on the spread of the COVID-19 pandemic in the UK at the MSOA level are provided by the Office of National Statistics (ONS). The number of COVID-19 cases in each MSOA is reported weekly, while COVID-19 related deaths are reported monthly for each neighborhood. In addition, the MSOA excess mortality in 2020 in respect to the 2018-2019 monthly average can also be calculated at the monthly level.

[FIGURE 1 HERE]

As shown in Figure 1, it is possible to notice stark differences in the number of COVID-19 cases and deaths across neighborhoods, even between closely located ones within the same local authority district. For instance, we can see that while COVID-19 cases seem to be mostly clustered in the east and west of the Greater London Authority, among the most deprived areas of the city, COVID-related deaths are much more sparsely distributed, even in more affluent neighborhoods in the south of the city.

3.2 Urban Density

To measure urban density we first use satellite imagery data, following novel approaches in urban economics (Henderson et al., 2019; Roca and Puga, 2016), allowing for finer level of granularity filling gaps in more conventional datasets. We first use data from the GHS-POP spatial raster dataset on the distribution of people per 1 squared kilometer cell for each month in 2015 (Schiavina et al., 2019). This variable represents an ambient population distribution averaged over 24 hours and it is estimated using census demographic and geographic data together with remote sensing imagery analysis techniques[3]. In addition, we use data from the ENACT-POP spatial raster dataset capturing the seasonal nighttime and daytime changes in the number of people per squared kilometer in 2011 (Schiavina et al., 2020).[4] Despite the lack of recent updates in the data, this dataset is useful for distinguishing between where people live (proxied by nighttime population) and where people usually are during the day due to work, schooling or leisure (proxied by daytime population). These data also allow us to check for month by month seasonal adjustments in these two dimensions[5]. We find that population density is quite different across neighborhoods at daytime and nighttime; population is clustered in city centres neighborhoods during the day,

[3]We use LandScan data on the global population distribution at approximately 1 squared kilometer spatial resolution for 2019 as an alternative sources of satellite data in order to check consistency. For more information regarding the LandScan data please refer to `https://landscan.ornl.gov/`.

[4]We transform the satellite data at the MSOA level by populating the MSOA polygons with data from the 1 kilometer squared raster layer taking in account the proportion of the raster cell that each polygon covers.

[5]For more information regarding the GHS-POP and the ENACT-POP data please refer to `https://ghsl.jrc.ec.europa.eu/datasets.php`.

but more densely located in suburban areas at night (Figure A1 in the Appendix). This highlights the importance of disentangling between where people live and work, especially when studying the relevance of social interactions within and between households in explaining the spread of viral diseases.

We also calculate urban density in a more conventional way, using population and employment counts provided by the Office for National Statistics (ONS). Residential population counts are based on 2019 population estimates, while employment counts by occupation are based on the 2011 population census. For residential population density we have information at the level of lower super output level (LSOA). Each LSOA is contained exclusively within a single MSOA. This allows us to calculate a more precise measure of geographic density following Glaeser and Kahn (2004). We calculate density for each MSOA as the weighted sum of residents per hectare for all LSOAs within the MSOA:

$$Pop.Den_i = \sum_{j \in MSOA_i} \frac{N_j^r}{Area_j} \times \frac{N_j^r}{N_i^r}, \tag{1}$$

where N_j is the LSOA population and N_i is the MSOA population. $Pop.Den_i$ is therefore the average density of all LSOAs within MSOA weighted by population share. We calculate a similar measure for employment density. However, because employment information is only available at the MSOA level, we calculate the simple measure of workers per unit of land area:

$$Emp.Den_i = \frac{N_i^w}{Area_i}, \tag{2}$$

Figure 2 reports the different distribution of population and employment density across neighbourhoods in the Greater London Authority, showing a strong concentration for both measures at the centre of the city. This evidence shed a light on how these measures might not be capturing effectively the distribution of where people live and where they work. Even more importantly, the comparison with Figure 1 shows a very low spatial correlation between the distribution of COVID cases and deaths, mainly clustered in suburban and peripheral areas, and of population and employment density, mostly concentrated instead in the city centre. This indicates that different measures of the spatial distribution of urban density should be considered, taking into consideration the characteristics of the residents and workers population that are more related with the spread of the virus.

[FIGURE 2 HERE]

3.3 Residents and Workers Local Labour Market Composition

We start by measuring the employment compositions of residents and workers in each neighbourhood. We use data from the ONS Nomis Official Labour Market Statistics to decompose the residential population, N_i^r, and the working population, N_i^w (some of whom may also be residents), into the following groups:[6]

$$\begin{aligned} N_i^r &= NW_i^r + KW_i^r + HW_i^r + OW_i^r, \\ N_i^w &= KW_i^w + HW_i^w + OW_i^w. \end{aligned}$$

The variable KW measures the number of people in an occupation denoted as *key work*, such as hospital staff, primary education, critical retail and public transport workers, and would have likely continued working onsite through pandemic lock-downs. In contrast, homeworkers, HW, are the number of people who would have been able to do a significant portion of their job from home. Finally, all other workers, OW, denotes the number of people employed in non-essential work that is unlikely to be done from home. This final category would for instance include many workers in retail and hospitality. In addition, NW_i^r is the number of residents in the neighborhood who do not work, including children and retirees. Of course, we only observe this group for the residential population, not the working population.

For four-digit occupation classifications (SOC) we define occupations as being able to be done from home following the classification introduced in Dingel and Neiman (2020) and adapted for the UK occupation classification in De Fraja et al. (2021). This assigns each occupation with an index value reflecting the proportion of the job that can be done from home. An occupation is defined as *key work* if it cannot be done from home and is identified as a key work job on the nationally published Key Work Reference Tables (ONS, 2020), which identify the occupations which where legally allowed to continue working during the national lockdowns. We provide details of the assignment of occupations to each group, as well as a table of representative jobs for each group, in the supplementary appendix.

[FIGURE 3 HERE]

In respect to Figure 2, Figure 3 shows a much more nuanced distribution of where *keyworkers* or people able to work from home live and where they work across neighborhoods in the Greater London Authority. In particular, we notice that the share of resident *keyworkers* is particularly

[6] More information regarding the calculation and definition of the residents and workers types can be found in the Appendix.

high in neighborhoods outside the city centre, especially in the east side of the metropolitan area, characterised as well by higher levels of economic deprivation. This is in strong contrast to MSOAs with a higher percentage of workers that could work from home, reported on the right of panel a). Similarly, we observe a more sparse distribution of where *keyworkers* work, not identifying specific spatial clusters, while the workplaces of employees able to work remotely are mostly concentrated in the central business districts and in the south-west of the city, reflecting the distribution of white collar jobs.

3.4 Other Data

Finally, we gather additional data about the characteristics of neighborhoods that might explain the spatial spread of the virus within cities. First, we obtain further information on neighborhoods resident population from the Office for National Statistics Nomis dataset, as the portion of residents under 18 years old, the proportion of residents over 65 years old, and the share of white ethnicity over total population. Second, we collect additional information on other neighborhood socio-economic characteristics. We measure house crowding, calculated as the number of people per square meter of residential buildings, using additional data from the Valuation Office Agency. Neighbourhood deprivation level is taken into account using the Ministry of Housing, Communities Local Government's English Indices of deprivation.[7] The level of particulate matter 2.5 pollution is measured using data from the Department for Environment, Food & Rural Affairs (DEFRA) to proxy for pollution. Finally, we include information on the number of care beds available in each neighborhood collected by the National Health Service (NHS).

4 Empirical strategy

4.1 Baseline Analysis

We first look at the role of urban density in facilitating the spread of the COVID-19 virus, as similarly analysed in previous studies (Wong and Li, 2020; Allcott et al., 2020; Desmet and Wacziarg, 2021; Almagro and Orane-Hutchinson, 2020; Carozzi et al., 2020), by estimating the following baseline model:

$$COVID_{it} = \alpha_1 Density_{it} + X_i'\Gamma + \lambda_t + \theta_r + \gamma_{r,t} + e_{it}, \tag{3}$$

The dependent variable $COVID_{it}$ reflects the logged COVID-19 cases, plus one, for week (t) cases in each neighbourhood i. We mainly focus on cases given that this is the aspect of the

[7] Maps for deprivation and house crowding are reported in Figure A2 in the Appendix.

COVID-19 infection that mostly disrupt the usual functioning of the economy due to self-isolation, sick leaves and absenteeism. Therefore, by focusing on COVID-19 cases we aim to understand which group of workers across urban neighborhoods would need particular attention to minimise negative effect on the economy as the virus becomes endemic.[8] The primary independent variable of interest, $Density_{it}$ is the population density for neighborhood i. We consider several different measures of density including monthly satellite imagery data, satellite imagery data for day and nighttime population density, and using population and employment counts per squared kilometer as previously defined in the data section.

We include controls for a number of neighborhood characteristics in X_i, including log-population and log-employment counts, the portion of residents under 18 years old, portion of residents over 65 years old, the share of white ethnicity, house crowding, neighbourhood deprivation, particulate matter 2.5 pollution, the number of care beds available, and spatial lags of the number of COVID-19 cases in other neighborhoods within the same local authority district weighted by the pair-distance between neighborhoods.

We control for unobserved time-variant heterogeneity at the local government level by including city fixed-effects θ_r, time fixed-effects λ_t, and local authority time trends γ_{rt}[9]. Residual time-and-neighbourhood varying observable factors are included in the term e_{it}. The coefficient of interest, α_1, is identified off the within-city neighborhood variation in population density prior to the pandemic.

4.2 Local Labour Market Composition Analysis

We want to disentangle the role of urban density and the role of employment compositions in facilitating the spread of the virus. Specifically, we may expect that neighbourhoods in which many workers can do their jobs from home to have a different level of contagion than neighbourhoods in which many workers continue to work onsite. To do that, we modify Equation 3 by decomposing the residential (r) population in a neighbourhood i (N_i^r) into the number of resident homeworkers (HW_i^r), keyworkers (KW_i^r) and residents who do not work (NW_i^r). Similarly, we split the number of employees working (w) in a neighbourhood i into workers able to do a substantial part of their job from home (HW_i^w) and employed keyworkers (KW_i^w). We account for the distribution of the residents and workers populations across these different employment types in our regression analysis as follows, where the variables are included in log terms:

[8] While our primary outcome reflects the weekly number of cases, in the appendix we include several robustness tests using as our outcome cumulative COVID-19 cases (Table A5 in the Appendix),the monthly number of COVID-19 deaths (Table A6), and the monthly excess mortality in 2020 in respect to the 2018–2019 monthly average (Table A7).

[9] Results are robust to controlling for local labour market idiosyncratic effects including instead Travel to Work Area (TTWA) fixed-effects.

$$
\begin{aligned}
COVID_{it} = \quad & \alpha_1 Popden_i + \alpha_2 HW_i^r + \alpha_3 KW_i^r + \alpha_4 NW_i^r + \\
& \beta_1 Empden_i + \beta_2 HW_i^w + \beta_3 KW_i^w + X_i'\Gamma + \lambda_t + \theta_r + \gamma_{r,t} + e_{it},
\end{aligned} \tag{4}
$$

Because we control for the total resident (worker) population in X_i, the coefficients α_2-α_4 (β_2-β_3) reflect the percent change in average Covid-19 cases from a one percent increase in the number of residents (workers) over residents (workers) in other non-essential onsite jobs (OW).

4.3 Additional Analysis

We perform several additional analysis to better understand some of the mechanisms linking the composition of the local labour market with the spread of COVID-19. First, we consider the dynamic evolution of the spread of the disease, following (Desmet and Wacziarg, 2021), and allow the model in Equation 4.2 to be fully flexible over time:

$$
\begin{aligned}
COVID_{it} = \quad & \alpha_{1,t} Popden_i + \alpha_{2,t} HW_i^r + \alpha_{3,t} KW_i^r + \alpha_{4,t} NW_i^r + \\
& \beta_{1,t} Empden_i + \beta_{2,t} HW_i^w + \beta_{3,t} KW_i^w + X_{i,t}'\Gamma + \gamma_{r,t} + e_{it},
\end{aligned} \tag{5}
$$

where variables are as specified above. In practice, we estimate this as a series of cross-sectional regressions for each time period, in order to track the evolution of the effect of population and employment density over time. This will give us the opportunity to test the efficacy of the public heath measures imposed by the UK Government to control the spread of the virus, such as as the restriction of working onsite to jobs identified as key worker only.

Secondly, we explore further the nature of key work and work done from home by distinguishing between different levels of skills intensity across occupations. This could further help us to analyse the heterogeneity within type of work done, especially when considering high-skilled (doctors, pilots etc.) versus low-skilled keyworkers (bus drivers, essential retail and deliveries).

Third, we explore the heterogeneity of our baseline results across different neighborhoods characteristics. In particular, we interact the main variables of interest with the index of multiple deprivation (IMD). This analysis will identify if the relationship between the local labour market composition and the spread of the virus is affected by the level of deprivation of the neighborhood, in particular when the spatial distribution of keyworkers is clustered around deprived areas. In addition, we combine this with the dynamic analysis of lockdown periods in order to understand whether public health measures introduced by the UK Government could have heterogeneous effects on limiting the contribution of the local labour market composition to the spread of the virus, depending on the socio-economic characteristics of neighborhoods. This analysis will inform us about the social justice implications of the national lockdowns imposed in the UK, which could affect disproportionately neighborhoods with higher levels of deprivation where most of the resident population are not able to work from home and have to resume working on site in order to avoid losing income. In an alternative specification reported in the Appendix we investigate as well the role played by house crowding in mediating the effect of population and employment density on the spread of the virus. A large number of people living in small and crowded places could significantly increase the COVID-19 contagion rate. This is particular relevant in the case of neighborhoods with high levels of resident keyworkers, who are forced to work onsite and ares exposed to social contact throughout the pandemic, and will be even more throughout the endemic phase of the disease. Keyworkers are more likely to bring the virus home from work, where it could easily spread due to the high concentration of people living in the same house, in particular in the case of multi-generation households.

Finally, on top of the robustness checks mentioned earlier, we perform several additional and sensitivity tests to validate our results. First, in Table A3 in the Appendix we replicate the local neighborhood employment structure results by using measures of the share of keyworkers, homeworkers and other workers over the total population of residents and workers rather than the count. Secondly, in Table A4 in the Appendix we make sure that our findings are not contaminated by the roll out of COVID vaccines provided to entire population for free in the UK starting from late December 2020, by excluding weeks from January 2021 onward. Finally, in Table A8 in the Appendix we look at the relationship between population, employment density, neighborhood labour structure and COVID-19 weekly cases by distinguishing between MSOAs in small and large TTWA commuting areas. This analysis will further inform us about how local neighborhood labour structures interact with the wider employment and population density in the commuting area in facilitating the spread of viral infections in densely or sparsely populated areas.

5 Results

5.1 Baseline Results

We start in Table 1 with our baseline panel regression model by analysing the effect of urban, population and employment density on the weekly spread of COVID-19 cases. Column 1 follows Equation 3 considering urban density measured using satellite data, then split in daytime and nighttime density in column 2. Column 3 differentiates between the role of population and employment density, while column 4 reports the results of regression model 4.2 where we consider as well the composition of resident and employed keyworkers and homeworkers at the MSOA neighborhood level.

[TABLE 1 HERE]

Urban density is significant in explaining higher levels of COVID-19 cases across neighborhoods, although the magnitude of the effect is relatively small. On average, one percent increase in urban density measured using satellite data in Column 1 is associated with a 0.065 percent increase in cases. As shown in Column 2, this effect is mostly driven by nighttime population density rather than daytime, suggesting a stronger role played by residential density. However, in Column 3 we find that both population and employment densities are significant in explaining the viral spread, consistent with previous studies based on standard measures of population density (Wong and Li, 2020; Allcott et al., 2020; Desmet and Wacziarg, 2021; Almagro and Orane-Hutchinson, 2020), as well as research on manufacturing employment density (Ascani et al., 2021). Interestingly, the coefficients for both variables are of similar magnitudes.[10] The remaining control variables included in our models are significant and in line with previous studies investigating their relationship with COVID-19.[11]

In Column 4, we present the results for estimating Equation 4.2. Conditioning on the types of workers in a neighborhood, employment density and residential density are significant in explaining COVID-19 cases. We find statistically significant and economically meaningful results for the resident labour force composition. A one percent increase in the number of residents able to work from home, as opposed to residents working in other non-keywork jobs, is associated with a 0.087 percent decrease in COVID-19 cases. Based on the mean values (Table A2 in the Appendix), this roughly translates to a decrease of 1 case a week for each additional 47 residents working from home. In contrast, an increase in the proportion of resident keyworkers is associated with

[10] Although population density seems to matter more than employment in neighborhoods part of large commuting areas, as shown in Table A8 in the Appendix.

[11] Further, results are generally consistent when considering the cumulative measures of COVID-19 cases over this period (Table A5 in the Appendix), the monthly number of COVID-19 deaths (Table A6) and monthly excess mortality (Table A7).

an increase in Covid-19 cases. 47 more resident keyworkers in a neighborhood will lead to an increase of almost 2 COVID cases per week. We interpret these results as showing that by working from home, residents in a neighborhood can slow down the infection, preventing the spread of the virus from the place of work to the place where they live, while the opposite holds in the case of keyworkers who keep working onsite through the pandemic.

We find similar results for the employment composition of people working in a neighbourhood. An increase in the proportion of workers able to work remotely from home reduces the infection incidence in the local population, while an increase in keyworkers employed in the neighborhood increases the incidence of COVID cases across local residents, despite its statistical significance is weaker in respect to other estimates. Specifically, we find an elasticity of -0.040 for home work jobs, or 71 more jobs that can be done from home will decrease by COVID case by 1 per week in the workplace neighborhood. We find a positive effect of similar magnitude for keyworkers, where 71 more keyworkers employed in a neighborhood would translate into 0.96 more cases per week among the local resident population.

A simple back of the envelope calculation based on our estimates could help us to gauge the relative importance of the local labour market composition in explaining differences in the number of COVID cases between neighborhoods. Following our empirical approach, we compare the cumulative number of COVID cases over the period and the number of resident and employed keyworkers and homeworkers between all combinations of MSOAs, which on average have similar population sizes, within each LAD in England. In this way we are able to calculate the share in the difference of COVID cases which can be explained by the difference in the number of residents and workers in each job type for all combinations of MSOAs in each LAD.[12] We calculate that on average within LAD differences in number of keyworkers across MSOAs explain about 3.6% of the differences in the cumulative number of COVID cases over our period of analysis (this is 2.05% in the case of keyworkers employed in the neighborhood). On the contrary, larger positive differences in the number of residents homeworkers explain almost 1.1% of the smaller number of COVID cases between neighborhoods (2.7% in the case of differences in the number of employed workers able to work from home). As an example, we compare two MSOAs with a similar overall population size within the same LAD of Greenwich in London: the first one, Eltham North in the 25th percentile of the national distribution of resident keyworkers (652) and with a cumulative

[12]For all MSOAs i and j combinations in each LAD r we calculate this as the difference in the number of keyworkers(homeworkers) residents(workers) (L) multiplied times the relevant β^L coefficient estimated from Equation 4.2 and reported in Column 4 of Table 1, divided by the difference in the cumulative number of COVID cases over the period March 2020-April 2021 (C): $\frac{\sum_{ijr} \frac{(L_{ir}-L_{jr})\times\beta^L}{(C_{ir}-C_{jr})}}{N_{ijr}}$.

number of 481 COVID cases; and the second one, Abbey Wood North in the 75th percentile of the distribution with 955 resident keyworkers and 854 cases overall. Our calculations show that based on our estimates the larger number of resident keyworkers in Abbey Wood could explain 5.8% of the difference in COVID cases in respect to Eltham North. This exercise shows the significance of the local labour market composition in explaining within cities differences in the spread of the virus, on top of the traditional measures of density and the other main drivers analysed by the literature so far.

5.2 Additional Results

Dynamic and Lockdown Analysis

We try to explore some of the mechanisms at play linking the labour composition of neighborhoods with the spread of the COVID-19 virus performing several analysis. First, in Figure 4, we examine the dynamic variation in the effect of the number of resident and employees key and homeworkers with respect to changes in public heath measures imposed by the UK Government. In the left panels, we report results for keyworkers, while results for WFH are reported on the right. To ease the comparability, all estimates are reported as standardised beta coefficients. We observe clear differences in the relationship between employment structures and cases during lockdown periods (March-July 2020 and November 2020-April 2021) and during the opening period (July-November 2020). In particular, cases are significantly higher in neighbourhoods with more resident keyworkers during lockdown periods. This could be an evidence that the presence of keyworkers resident in a neighborhood, who had to keep working onsite throughout the pandemic and have been more exposed to the contagion risk, could be a significant driver of viral transmission in the neighbourhoods where they reside. Interestingly, we observe a negative effect for resident keyworkers in the opening period. This may be related to the precautions as well as health measures keyworkers had to follow throughout the pandemic to reduce the risks of infection inherent to their jobs. Such effect may also be due to the greater social interaction associated with jobs in the reference group, non-essential onsite workers, which includes occupations in the hospitality and retail industry (see Table A1 in the Appendix). In fact, previous studies have shown how the publicly subsidised economic activity in these industries has helped the spread of the virus when they reopened in between national lockdowns in 2020 (Fetzer, 2021). The effects are instead smaller and statistically weaker when looking at the role of employees keyworkers, with an initial increase in cases in the first months of the first lockdown, whilst almost no effect in the following months.[13] We find the opposite patterns for residents and employees who could work from home.

[13]Such difference may reflect the fact that keyworkers were likely to have been targeted for testing early in the pandemic, when testing was scarce. With respect to this, it should be noted that we cannot rule out that the role out of Covid-19 testing may be correlated with the spatial within-city distribution of keyworkers. However, it is

Here, cases clearly reduce during lockdown periods in neighborhoods where residents and workers are able to continue their economic activities from their dwellings without mixing with other households, while we observe almost no effect when social restrictions are lifted. Overall, these results complement previous evidence (Di Porto et al., 2022) underlining the importance of disentangling the analysis of viral transmission with respect to where people live and where they work.

[FIGURE 4 HERE]

Crucially, our findings provide some evidence of a trade-off in the shielding effect of lockdowns, as an increased protection for workers able to work from home and for the communities where they live and work has to be evaluated with respect to an increase in cases in neighbourhoods with a higher share of resident keyworkers. This suggests employment structures carry important implications related to social justice in the public health measures introduced by many governments in their efforts to stop the spread of viral infections.

Heterogeneity Analysis

We further explore this aspect by looking at the heterogeneity of these results across the neighborhoods deprivation distribution. In Figure 5, we interact our key variables of population and workers employment structure with the four quartiles of the index of multiple deprivation distribution. Our results show evidence of heterogeneous effects of residents employment composition on COVID-19 cases across deprived neighborhoods. We observe that the number of resident keyworkers in a neighborhood significantly increases the incidence of COVID-19 cases particularly in the most deprived MSOAs (fourth quartile - Q4). On the contrary, a larger number of residents working from home significantly reduces infections, more markedly in the most affluent areas (first quartile - Q1). Again, these results have important policy implications in terms of the social justice of policies addressing viral diseases. In particular, residents in deprived areas are more likely to have keywork jobs that require onsite presence throughout the pandemic, increasing their social interactions. As a consequence, our results indicate that keyworkers resident in these areas might have been more likely to bring the virus home from work, increasing the likelihood of viral transmission to the rest of the local community. This interpretation partly reflects the relationship between neighborhood deprivation and the high concentration of people living in the same house, in particular in the case of multi-generation households, as indicated by robustness analysis on house-crowding heterogeneity (see Figures A2 and A3 in the Appendix). On the contrary, we do not find clear evidence of heterogeneous effects in the case of the employment composition of

important to point out that by the time of the second lockdown, testing was fully rolled out and widely available.

workers in a MSOA, driving the incidence on COVID cases both for key and remote workers only in relative well-off neighborhoods in the second quartile of the distribution.

[FIGURES 5 and 6 HERE]

We further investigate the role of neighborhood deprivation in Figure 6 by analysing whether the public health measures introduced by the UK Government have heterogeneous effects on limiting the contribution of residents and workers employment structure in spreading the virus in a neighborhood depending on its level of deprivation. This analysis could provide further information about the social justice implications of national lockdowns introduced by governments. Evidence form Figure 6 indicates that the previously discussed insights hold true in particular during lockdown periods, when keyworkers are the only ones required to work onsite. However, differently from Figure 5, we do not observe significant differences across quartiles of deprivation distribution. As already suggested by Figure 4, we instead observe a significant decrease in cases in MSOAs with a higher number of resident keyworkers outside lockdown periods, which likely reflects the reduced social interaction of keyworkers with respect to the reference group of non-essential onsite occupations, including workers in retail and hospitality. We note that such result does not hold for resident keyworkers in the most deprived neighborhoods, which might point to the fact that keyworkers resident in these neighborhoods keep spreading the virus to their communities also during non-lockdown periods as much as non-essential workers more exposed to social interactions in the hospitality sectors. This could explain the overall stronger relationship between resident keyworkers and infection cases in most deprived neighborhoods estimated in Figure 5. Results differ when considering employed keyworkers, pointing once again to the importance of considering where people live as opposed to where they work. Conversely, larger shares of residents working-from-home reduced the incidence of COVID-19 during lockdown periods, particularly in the least deprived areas. We do not find statistically significant differences outside lockdowns for residents and employees WFH, suggesting working form home without the additional effect of lockdowns may not be a significant element in reducing viral transmission across the population. Overall, these results point to the presence of trade-offs in the introduction of lockdowns. These policies may have shielded people that could work from home and their communities in the most affluent areas, but they could also have increased the relative exposure and risk of contagion to more deprived neighborhoods with a higher share of resident keyworkers.

Skills Intensity Analysis

Given the strong heterogeneity in the relationship between keyworkers, homeworkers and viral infection across the deprivation distribution, we further investigate the different nature of keywork jobs done in rich and poor neighborhoods across the country in order to offer additional evidence on the consequences for the local residents of these areas. As shown in Figure 7, there is indeed a strong relationship between keywork occupation types and neighbourhood deprivation, where routine keywork occupations are mainly prevalent in disadvantaged areas. This is also shown in Table 2, where we observe the percentage of top 5 most concentrated keyworker occupations in the top and bottom quartiles of neighbourhood deprivation. A much larger proportion of care workers and home carers lives in the bottom quartile as opposed to the first, whilst the opposite holds for secondary education teaching professionals. We also show the most concentrated keywork occupations across the four quartiles in Table 3. Here, it is straightforward to notice marked differences in occupations, with over 40% of highly skilled jobs as aircraft pilots and flight engineers, managers and directors living in the most affluent areas, whilst less than 10% reside in the lowest quartile. Conversely, over 40% of people employed in low skill occupations such as street cleaners, food process operatives or hospital porters live in the lowest quartile of neighbourhood deprivation as opposed to just over 10% in the top quartile.

[FIGURE 7 HERE]

[TABLES 2 and 3 HERE]

We start exploring the potential implications for the spread of viral infection of such differences in the distribution of high and low skilled key work jobs across neighborhoods in Table 4. Here, for each keywork/homework occupation type for residents and workers we distinguished between high, medium and low skilled occupations. It is evident that viral infection in neighborhoods is mainly driven by medium and low-skilled keyworkers, both living and working in the area, such as food process operatives, hospital porters, cleaners and low skilled occupations in logistics. In addition, having a larger number of medium and low skilled workers able to work from home reduces infection in the workplace neighborhood. In line with this, we find an increase in cases for places with more low-skilled residents who could work from home. This could be driven by workers in these occupations that might have been pushed to work on site in order to avoid losing income. On the contrary, the positive effect of residents working from home in the reduction of infection in their neighborhood is driven only by high-skilled professionals, which are primarily living in the most affluent neighborhoods as previously shown. These findings suggest that the uneven relationship between occupation type and viral infection across neighborhoods could be primarily driven by the different skill intensity of the keywork and homework jobs done, and their unequal concentration across people living and working in different areas of cities. In Table A9 in the Appendix we corroborate how these findings are mainly driven by lockdown periods, similarly to the previous evidence discussed in Figure 6. These results highlight once again how the implementation of lockdowns has significant implications in terms of social equity, with heterogeneous effects due to spatial variation in the skill intensity of keywork and homework occupations of residents and workers across neighborhood.

[TABLE 4 HERE]

Finally, in Figure 8 we investigate how the role of jobs skill intensity varies across neighborhood deprivation levels. Figures in panel (a) for residents show that higher COVID cases incidence in a neighborhood is mainly explained by larger numbers of high-skilled keywork residents living in most deprived areas. Analysing the data we find that these relate mostly to jobs as medical practitioners, nurses, protective services and care workers, all professions highly exposed to contagion risks during the pandemic. This effect might be significant only in most deprived areas possibly because of the high level of crowding in multi-generational housing, particularly common in deprived areas, which could have facilitated the spread of the virus from the workplace of these residents to the local community. On the contrary, we do not find any significant difference for low-skilled resident keyworkers across the deprivation distribution.

[FIGURE 8 HERE]

In addition, we can notice that the negative relationship between resident homeworkers and COVID cases is particularly strong in the case of high-skilled workers living in the most affluent neighborhoods in the city, providing evidence corroborating the hypothesis previously discussed. However, when focusing on low-skilled resident homeworkers, we find a small but positive relationship with COVID cases in particular in affluent neighborhoods in the city. These are predominately jobs is in sales, including elementary sales, stock control clerks, collector salespersons and credit agents. It might be possible that given the nature of these jobs these workers have been asked by their companies to resume onsite work sooner than other high and medium-skilled homeworkers, exposing them to contagion risk and helping the virus to spread in low-deprivation neighborhoods.

When looking at the workers population in panel (b), we do not observe significant heterogeneity of workers skill intensity across neighborhoods deprivation. The only exception is the case of low-skilled jobs in the most deprived areas, where having a large number of low-skilled keyworkers working in the neighborhood would significantly increase the spread of the virus, while if low-skilled workers are able to work from home would reduce the contagion in the workplace neighborhood. Figure A5 in the Appendix confirms that these findings hold true mostly during lockdown period, while Figure A4 shows that these results are overall consistent when considering the heterogeneity across neighborhoods based on the house crowding distribution.

6 Conclusions

In this paper, we contribute to the growing literature on the role of the local economy structure in pandemic outbreaks of infectious diseases, by exploring the marked spatial variation in economic activities and local labour market composition. We provide novel evidence on the role of density in the COVID-19 pandemic. Exploring data at the neighbourhood (MSOA) level in England for the period between March 2020 and April 2021, we disentangle the relationship between density and COVID-19 cases and deaths along four related dimensions.

First, we extend recent findings pointing to the need to explore density at a granular micro level due to the highly localised nature of the transmission mechanisms of the SARS-CoV-2 virus (Glaeser and Kahn, 2004; Sá, 2020; Almagro and Orane-Hutchinson, 2020), and show that density at the neighbourhood level is a significant factor for transmission. Using satellite imaging data, we show this is especially the case at night, reflecting the impact of intra-household contagion. Additionally, we reinforce evidence indicating household crowding to be a key driver for COVID-19 diffusion (Desmet and Wacziarg, 2021; Almagro and Orane-Hutchinson, 2020).

Second, we further underline the importance to look beyond population density and consider the role of occupational structure and industry agglomerations. Our findings point to a general role of employment structure of workers as well as residents in an area, suggesting a role of employment density in the spread of the virus. More importantly, we highlight that density of keyworkers is a significant driver of both COVID-19 cases and deaths. This is a critical element considering these workers provide an essential service which cannot be be done remotely working from home and thus are required to carry on working onsite throughout the pandemic.

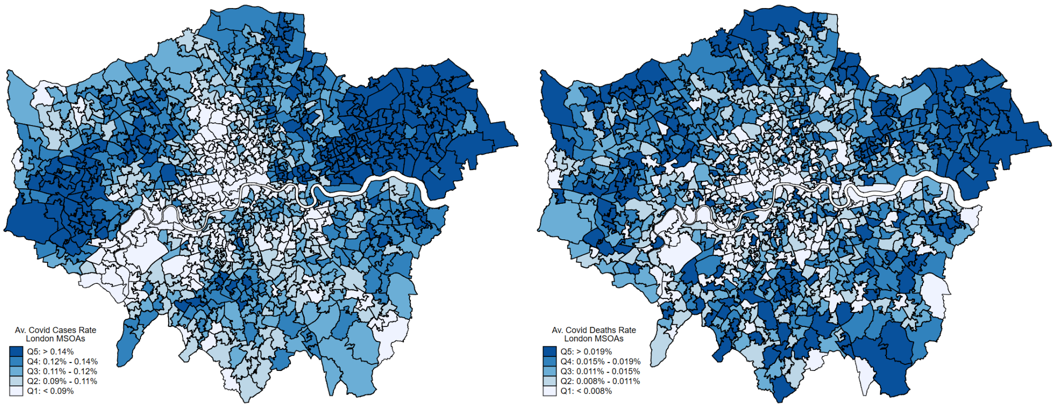
Third, while previous papers have highlighted the role of income distribution across places as a significant element in the COVID-19 pandemic (Desmet and Wacziarg, 2021; Rodríguez-Pose and Burlina, 2021), we provide novel findings pointing to a significant increase in risk across neighborhoods in England characterised by a large population of keyworkers in the lowest quartile of income distribution, health and housing deprivation. This evidences that the relationship between high concentrations of resident keyworkers who are not able to work from home that often live in more deprived areas may constitute a particularly significant element in the spread of the pandemic, with important implications from both public health and social justice perspectives. This is mainly driven by medium-low skilled keyworkers, mainly living in the most deprived areas in our cities, while the positive effect of working from home in limiting the contagion is felt only in affluent areas with a large number of high-skilled homeworkers.

Finally, we complement research on the role of public health measures on mobility restrictions such as lockdown policies and stay-at-home orders (Glaeser and Kahn, 2004; Almagro and Orane-Hutchinson, 2020; Bourdin et al., 2021; Allcott et al., 2020). In particular, we show how lockdowns have played a significant role in breaking the link connecting density of *keyworkers* COVID-19, except for the most deprived areas. This partially support previous evidence (Almagro and Orane-Hutchinson, 2020) suggesting lockdowns may effectively reduce risks of contagion in public places or in the workplace, but their role may be more limited in preventing intra-household contagion in particular for the most vulnerable and exposed categories of low-skilled keyworkers. These findings have important policy implications for the social justice of public health policies, basically shifting the social and economic burden of viral infections from affluent neighborhoods characterised by a large share of high-skilled residents able to work from home to the most deprived areas within cities where most low-skilled keyworkers live.

These results provide important insights not just to better understand determinants of diffusion of the virus, but equally to understand which areas and group of workers could remain more at risk of health consequences and economic losses as we transition towards an endemic phase of the viral infection. In particular, our findings may allow to design policies considering a more nuanced role of the employment structure of residents and workers, accounting for the significant differences in changes to work on site between key and non-essential workers, as well as the relationship between these elements and the increased risks associated with residence in the most deprived neighbourhoods. These elements are essential to better design policies for preventing further negative economic shocks and implementing more effective lockdown and other public health policies which may target more precisely the neighborhoods more vulnerable from an economic as well as a contagion perspective. Our findings also provide insightful evidence to manage the return of a large mass of homeworkers to the office during the endemic phase, predicting how the virus could rapidly spread across the population, based on the skill-intensity of workers and the level of deprivation of the neighborhoods where they work and where they live.

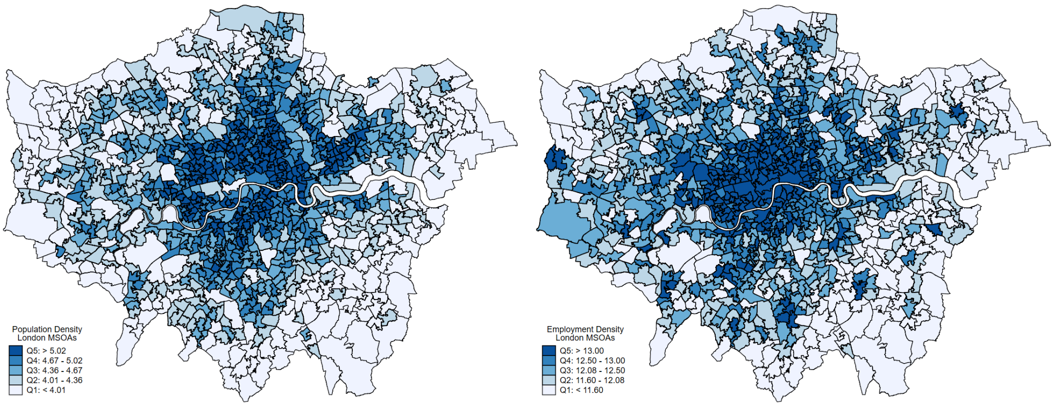
Tables and Figures

Figure 1: Average COVID-19 cases and deaths rates across MSOAs within the Greater London Authority.



Notes: Elaboration based on ONS data for the period March 2020-April 2021. Rates calculated over total population in 2019.

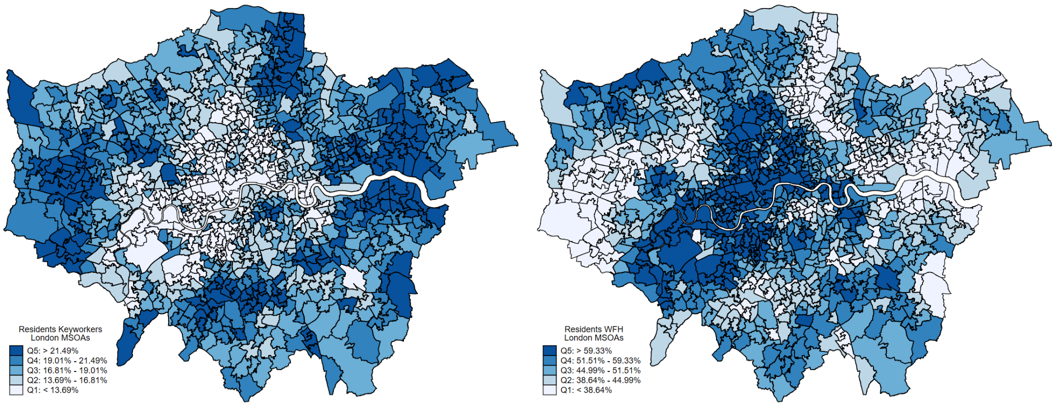
Figure 2: Population and Employment Density across MSOAs within the Greater London Authority.



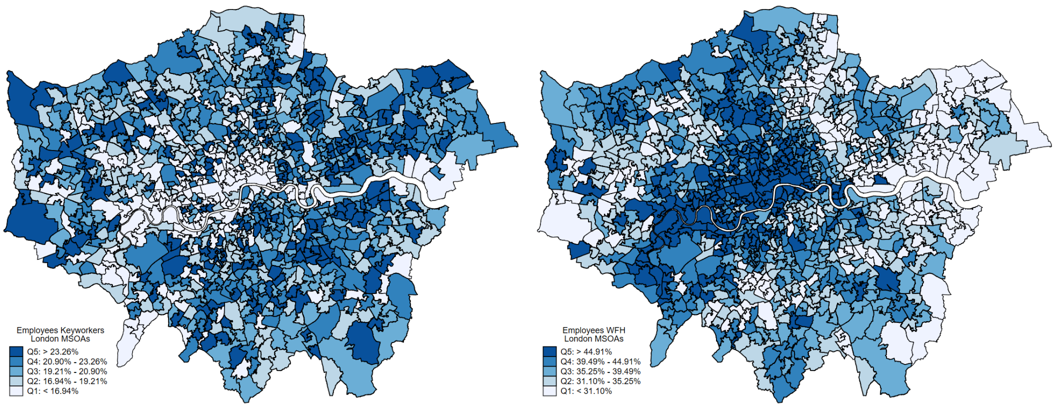
Notes: Elaboration based on ONS data for 2019. Density calculated over size of MSOA.

Figure 3: Share of residents and employees keyworkers or able to work from home (WFH) across MSOAs within the Greater London Authority.

a) Residents



b) Employees



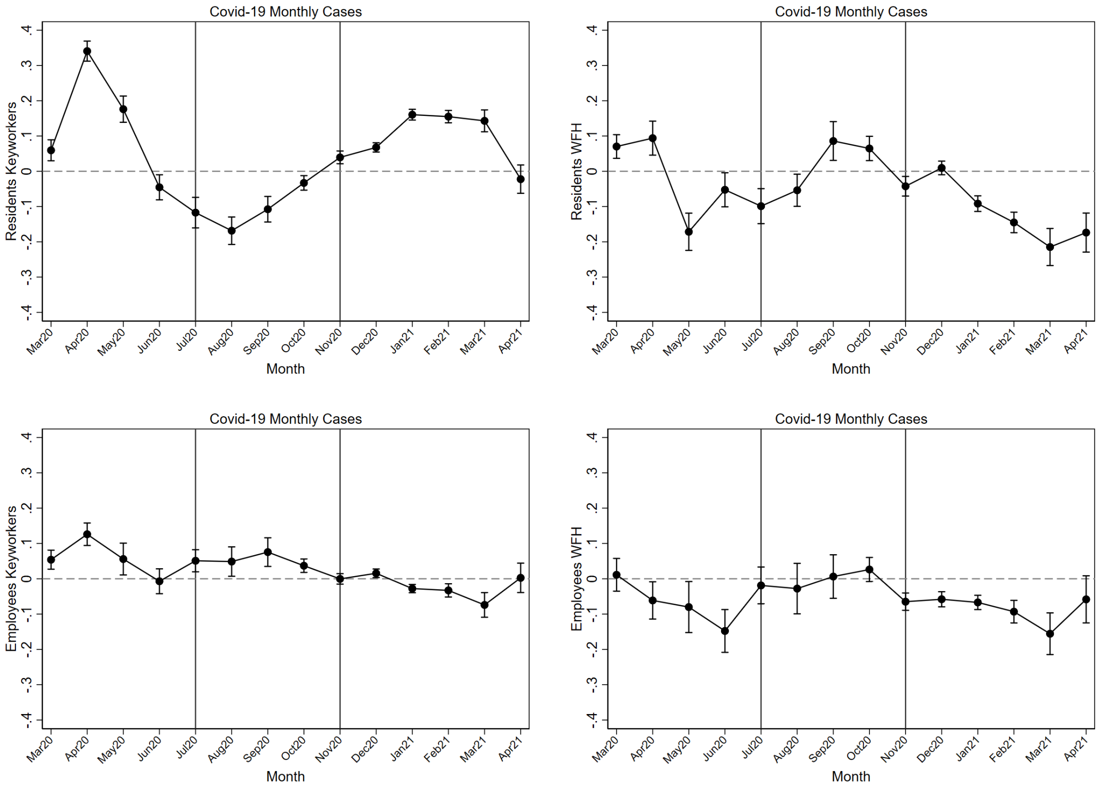
Notes: Elaboration based on ONS data for 2019. Shares calculated over total resident or working population in 2019.

Table 1: Relationship between population, employment density, neighborhood labour structure and COVID-19 weekly cases by MSOA.

	(1) Weekly Cases	(2) Weekly Cases	(3) Weekly Cases	(4) Weekly Cases
Satellite Density	0.0653*			
	(2.44)			
Daytime Density		-0.0154		
		(-1.83)		
Nighttime Density		0.0377**		
		(3.09)		
Population Density			0.0105**	0.00847*
			(2.85)	(2.25)
Employment Density			0.0149***	0.0159***
			(4.59)	(4.80)
Residents Keyworkers				0.0975***
				(4.74)
Residents WFH				-0.0867***
				(-3.62)
Employees Keyworkers				0.0228*
				(2.51)
Employees WFH				-0.0399**
				(-3.01)
Residents Not Employed				-0.0707
				(-1.48)
Population	0.604***	0.640***	0.663***	0.731***
	(22.74)	(48.64)	(64.34)	(8.62)
Employment	0.00425	0.00784*	-0.0000589	0.0215
	(1.39)	(2.03)	(-0.01)	(1.11)
Share Elderly	-0.0911*	-0.0691	0.116**	0.0793
	(-2.14)	(-1.64)	(2.66)	(1.69)
Share Children	0.465***	0.497***	0.492***	0.266**
	(5.26)	(5.42)	(5.18)	(3.04)
Share White	-0.525***	-0.520***	-0.503***	-0.530***
	(-20.42)	(-20.23)	(-19.53)	(-20.62)
House Crowding	0.0161	0.0185	0.0388**	0.0296*
	(1.28)	(1.47)	(2.89)	(2.22)
Deprivation Index	0.190***	0.190***	0.195***	0.0879*
	(10.08)	(10.12)	(10.23)	(2.41)
Pollution	0.0629***	0.0638***	0.0461***	0.0463***
	(14.52)	(14.70)	(9.89)	(9.93)
No. Care Beds	0.0177***	0.0177***	0.0167***	0.0163***
	(19.30)	(19.28)	(18.33)	(17.40)
Cases Spatial Lags	-0.00118***	-0.00117***	-0.00147***	-0.00145***
	(-8.10)	(-8.04)	(-10.08)	(-10.05)
LAD FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y
Observations	441285	441285	441285	441285
R^2	0.820	0.820	0.820	0.821

Notes: Robust standard errors clustered at the MSOA level. T-values reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

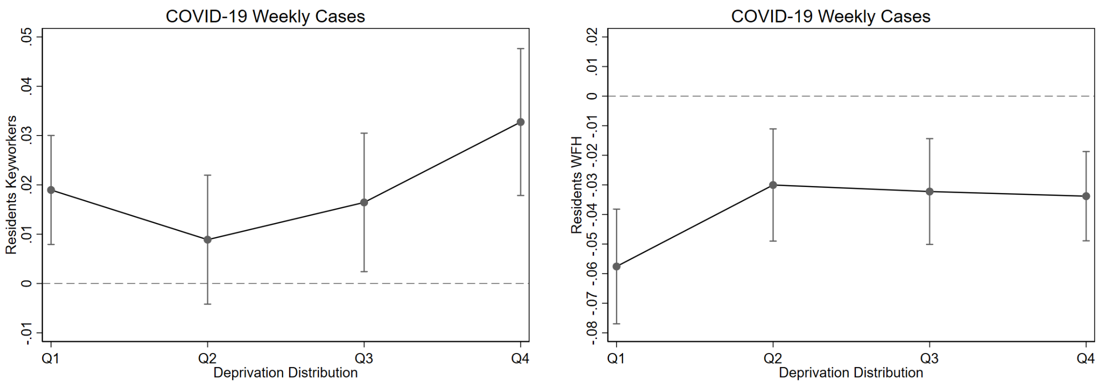
Figure 4: Dynamic relationship between neighbourhood labour structure and COVID-19 monthly cases.



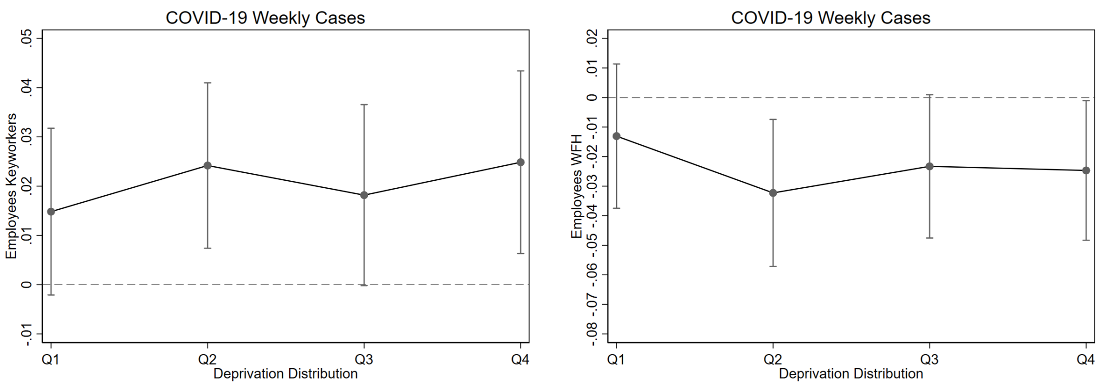
Notes: Markers represent beta coefficients from the log number of residents and employees in the MSOA who are defined as keyworkers or able to work from home. Different regression run for each month. Red lines show the end of the first national lockdown (04 July 2020) and the beginning of the second national lockdown (05 Nov 2020). Regressions control for local authority fixed effects, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA. Bars reflect 95% confidence intervals for coefficient estimates.

Figure 5: Relationship between neighbourhood labour structure and COVID-19 weekly cases across the neighbourhood deprivation distribution.

a) Residents



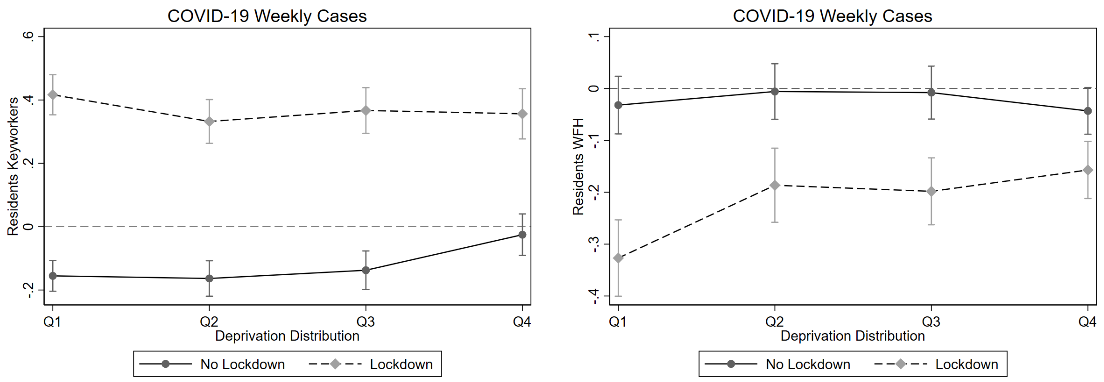
b) Employees



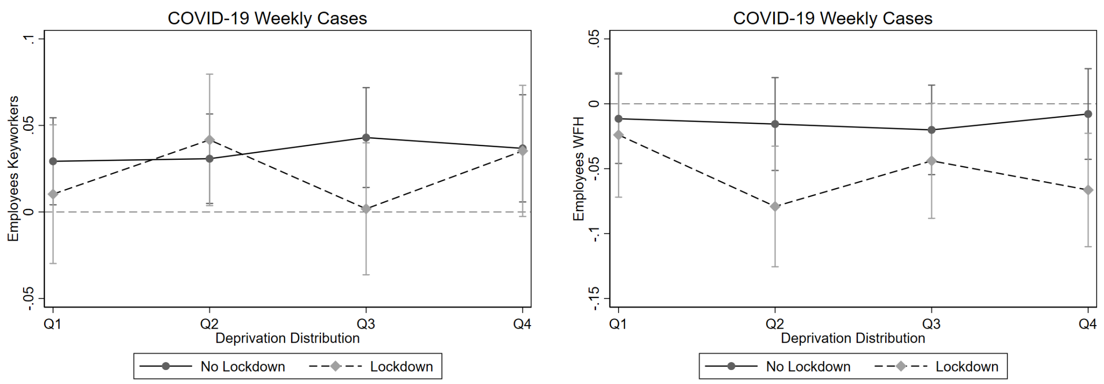
Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood deprivation distribution reported from least deprive (Q1) to most deprived (Q4) MSOAs. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Figure 6: Relationship between neighbourhood labour structure and COVID-19 weekly cases across the neighbourhood deprivation distribution during lockdown periods.

a) Residents

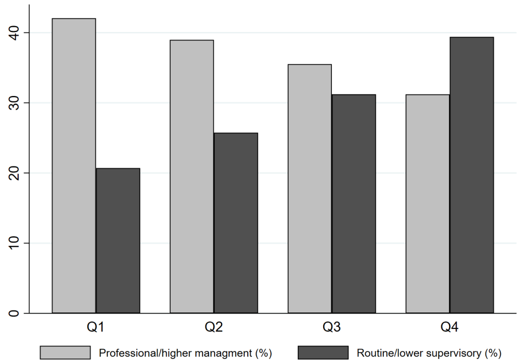


b) Employees



Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood deprivation distribution reported from least deprive (Q1) to most deprived (Q4) MSOAs. Lockdown periods considered are March-May 2020, November 2020, and January-April 2021. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Figure 7: Proportion of keywork by occupation type and neighbourhood deprivation.



Notes: Neighbourhood deprivation distribution reported from least deprive (Q1) to most deprived (Q4) MSOAs. Occupation classification according to the ONS National Statistics Socio-economic classification (variable *NSECM10*).

Table 2: Top keywork occupations, concentration by neighbourhood deprivation.

	Deprivation quartile			
Occupation	Q1	Q2	Q3	Q4
Care workers and home carers (2231)	4.47	6.29	7.90	10.89
Sales and retail assistants (7111)	4.92	5.54	6.55	7.82
Nurse (2231)	5.58	5.75	5.88	5.92
Protective services (311)	4.86	4.50	3.55	2.65
Secondary education teaching professional (2314)	4.74	4.09	3.44	2.52

Notes: This table reports, for the top 5 keywork occupations by percent of all keywork, the concentration of occupations according to neighbourhood deprivation. Each cell reports the occupation by percent of all keywork in the corresponding neighbourhood. UK Standard Occupational Classification (SOC) codes reported in parenthesis.

Table 3: Most concentrated keywork occupations by neighbourhood deprivation.

	Deprivation quartile			
Occupation	Q1	Q2	Q3	Q4
Aircraft pilots and flight engineers (3512)	52.04	31.41	12.01	4.54
Air traffic controllers (3511)	50.37	26.98	15.80	6.85
Information technology and telecommunications directors (1136)	47.00	28.46	16.91	7.63
IT project and programme managers (2134)	42.25	27.24	20.40	10.11
Financial managers and directors (1131)	42.17	29.11	19.43	9.29
Packers, bottlers, canners and fillers (9134)	9.54	16.98	28.22	45.25
Street cleaners (9232)	11.22	17.62	29.71	41.45
Fork-lift truck drivers (8222)	11.55	19.71	28.11	40.64
Food, drink and tobacco process operatives (8111)	10.14	20.07	29.72	40.07
Hospital porters (9271)	14.39	20.59	27.91	37.11

Notes: This table reports keywork occupation which are most concentrated in high and low deprivation neighbourhoods. Each cell reports the percent of jobs in the corresponding occupation that are in each deprivation quartile. UK Standard Occupational Classification (SOC) codes reported in parenthesis.

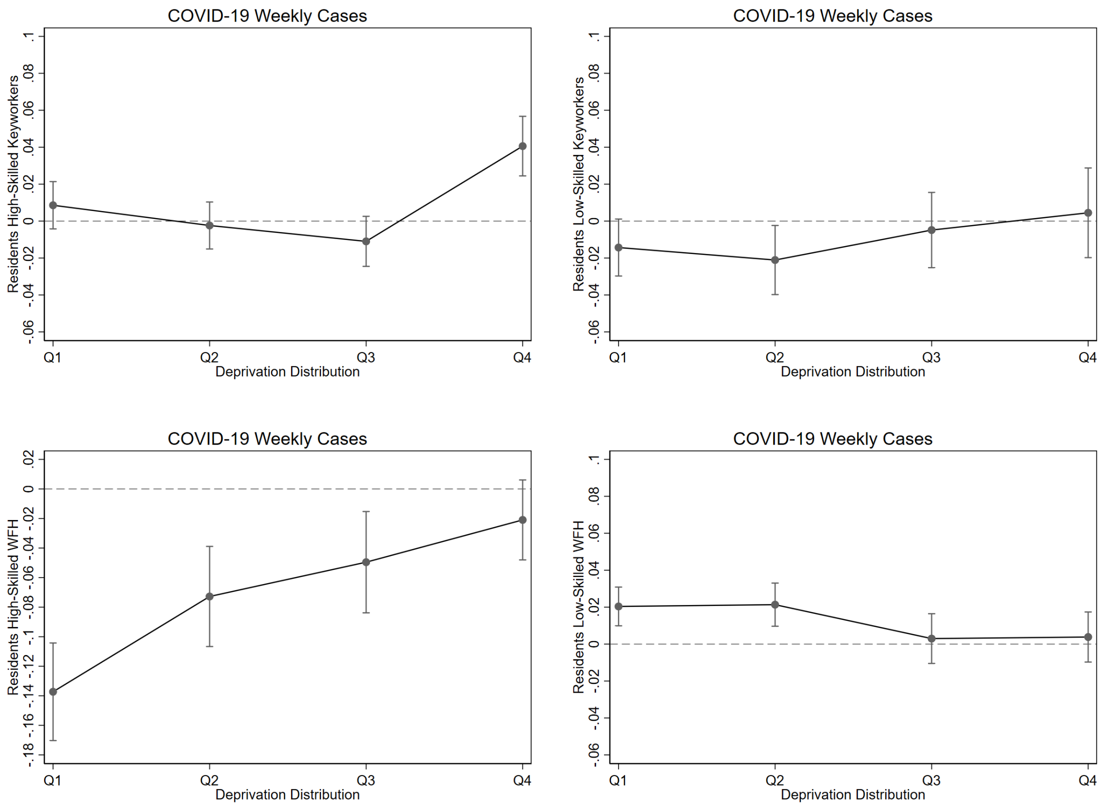
Table 4: Relationship between neighborhood labour structure and COVID-19 weekly cases by MSOA by occupation skill intensity.

Residents					
Keyworkers			*WFH*		
High-Skilled	Medium-Skilled	Low-Skilled	High-Skilled	Medium-Skilled	Low-Skilled
0.0208	0.0436**	0.0211*	-0.0901***	0.0260	0.0344**
(1.80)	(3.12)	(1.92)	(-4.21)	(0.93)	(2.80)
Employees					
Keyworkers			*WFH*		
High-Skilled	Medium-Skilled	Low-Skilled	High-Skilled	Medium-Skilled	Low-Skilled
0.0105	0.00490	0.0400**	0.0196	-0.0365**	-0.0256***
(1.54)	(0.70)	(2.74)	(1.29)	(-2.79)	(-3.65)
Observations : 441285 ; R-squared: 0.821					

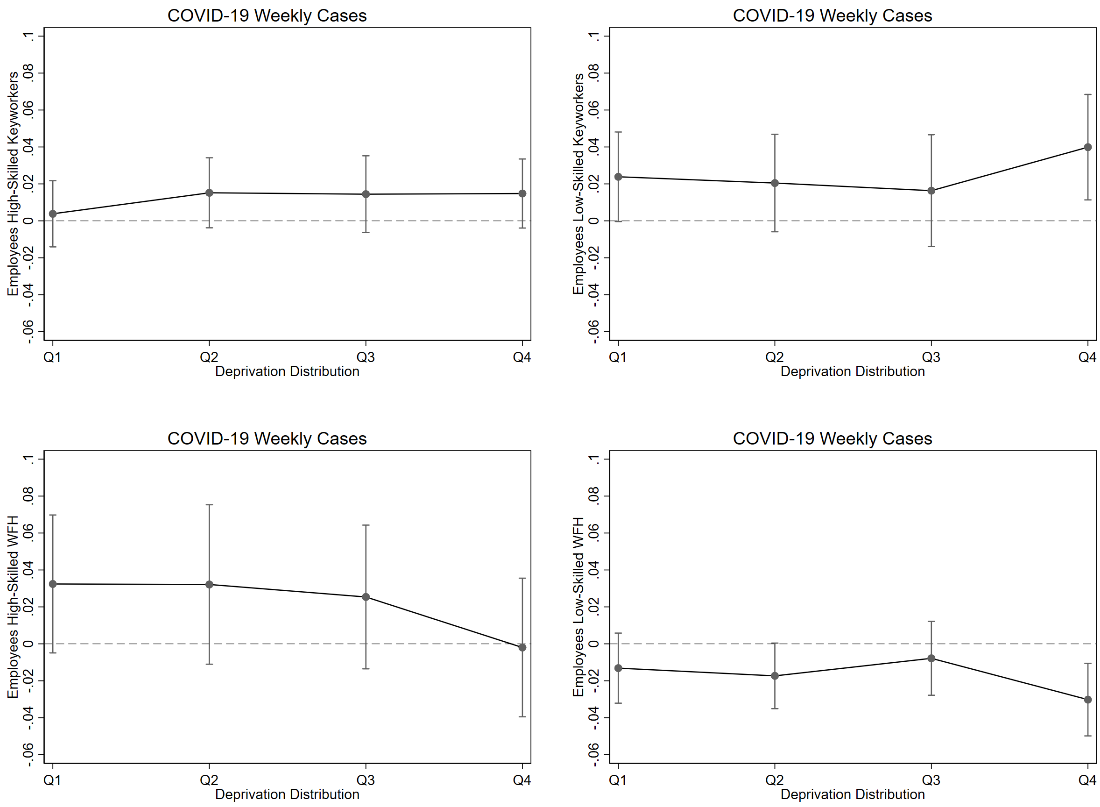
Notes: Robust standard errors clustered at the MSOA level. T-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Figure 8: Relationship between neighbourhood skilled labour structure and COVID-19 weekly cases across the neighbourhood deprivation distribution.

a) Residents



b) Employees



Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood deprivation distribution reported from least deprive (Q1) to most deprived (Q4) MSOAs. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

References

Acemoglu, D., Chernozhukov, V., Werning, I., and Whinston, M. D. (2020). *Optimal targeted lockdowns in a multi-group SIR model*, volume 27102. National Bureau of Economic Research.

Adams-Prassl, A., Boneva, T., Golin, M., and Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, 189:104245.

Allcott, H., Boxell, L., Conway, J. C., Ferguson, B. A., Gentzkow, M., and Goldman, B. (2020). What explains temporal and geographic variation in the early us coronavirus pandemic? Technical report, National Bureau of Economic Research.

Almagro, M. and Orane-Hutchinson, A. (2020). Jue insight: The determinants of the differential exposure to covid-19 in new york city and their evolution over time. *Journal of Urban Economics*, page 103293.

Alvarez, F. E., Argente, D., and Lippi, F. (2020). A simple planning problem for covid-19 lockdown. Technical report, National Bureau of Economic Research.

Armillei, F. and Filippucci, F. (2020). The heterogenous impact of covid-19: Evidence from italian municipalities.

Ascani, A., Faggian, A., and Montresor, S. (2021). The geography of covid-19 and the structure of local economies: The case of italy. *Journal of Regional Science*, 61(2):407–441.

Bailey, D., Clark, J., Colombelli, A., Corradini, C., De Propris, L., Derudder, B., Fratesi, U., Fritsch, M., Harrison, J., Hatfield, M., et al. (2020). Regions in a time of pandemic.

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., and Stanton, C. (2020a). The impact of covid-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, 117(30):17656–17666.

Bartik, A. W., Cullen, Z. B., Glaeser, E. L., Luca, M., and Stanton, C. T. (2020b). What jobs are being done at home during the covid-19 crisis? evidence from firm-level surveys. Technical report, National Bureau of Economic Research.

Bourdin, S., Jeanne, L., Nadou, F., and Noiret, G. (2021). Does lockdown work? a spatial analysis of the spread and concentration of covid-19 in italy. *Regional Studies*, pages 1–12.

Carozzi, F., Provenzano, S., and Roth, S. (2020). Urban density and covid-19. Technical report, IZA Discussion Papers.

Chang, S., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., and Leskovec, J. (2021). Mobility network models of covid-19 explain inequities and inform reopening. *Nature*, 589(7840):82–87.

Chowell, G., Bettencourt, L. M., Johnson, N., Alonso, W. J., and Viboud, C. (2008). The 1918–1919 influenza pandemic in England and Wales: spatial patterns in transmissibility and mortality impact. *Proceedings of the Royal Society B: Biological Sciences*, 275(1634):501–509.

Cole, M. A., Ozgen, C., and Strobl, E. (2020). Air pollution exposure and Covid-19 in Dutch municipalities. *Environmental and Resource Economics*, 76(4):581–610.

Correia, S., Luck, S., and Verner, E. (2020). Pandemics depress the economy, public health interventions do not: Evidence from the 1918 flu. *Available at SSRN: https://ssrn.com/abstract=3561560*.

Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., and Yelowitz, A. (2020). Strong social distancing measures in the united states reduced the covid-19 growth rate: Study evaluates the impact of social distancing measures on the growth rate of confirmed covid-19 cases across the united states. *Health Affairs*, 39(7):1237–1246.

De Fraja, G., Matheson, J., and Rockey, J. (2021). Zoomshock: The geography and local labour market consequences of working from home. CEPR Discussion Papers 15655, C.E.P.R. Discussion Papers.

Desmet, K. and Wacziarg, R. (2021). Jue insight: Understanding spatial variation in covid-19 across the united states. *Journal of urban economics*, page 103332.

Di Porto, E., Naticchioni, P., and Scrutinio, V. (2022). Lockdown, essential sectors, and covid-19: Lessons from italy. *Journal of Health Economics*, 81:102572.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, 189:104235.

Fattorini, D. and Regoli, F. (2020). Role of the chronic air pollution levels in the covid-19 outbreak risk in italy. *Environmental Pollution*, 264:114732.

Fetzer, T. (2021). Subsidising the spread of COVID-19: Evidence from the UK'S Eat-Out-to-Help-Out Scheme*. *The Economic Journal*. ueab074.

Garrett, T. A. (2007). Economic effects of the 1918 influenza pandemic. *Federal Reserve Bank of St. Louis*, 26.

Glaeser, E. L., Gorback, C., and Redding, S. J. (2020). JUE insight: How much does COVID-19 increase with mobility? evidence from New York and four other US cities. *Journal of Urban Economics*, page 103292.

Glaeser, E. L. and Kahn, M. E. (2004). Sprawl and urban growth. In Duranton, G., Henderson, V., and Strange, W., editors, *Handbook of Regional and Urban Economics*, volume 4, chapter 56, pages 2481–2527. North Holland, Amsterdam, Netherlands.

Guha, A., Bonsu, J., Dey, A., and Addison, D. (2020). Community and socioeconomic factors associated with covid-19 in the united states: Zip code level cross sectional analysis. *medRxiv*.

Henderson, J. V., Nigmatulina, D., and Kriticos, S. (2019). Measuring urban economic density. *Journal of Urban Economics*, page 103188.

Kuebart, A. and Stabler, M. (2020). Infectious diseases as socio-spatial processes: The covid-19 outbreak in germany. *Tijdschrift voor economische en sociale geografie*, 111(3):482–496.

McCann, P., Ortega-Argilés, R., and Yuan, P.-Y. (2021). The covid-19 shock in european regions. *Regional Studies*, pages 1–19.

McCann, P. and Vorley, T. (2021). *Productivity and the Pandemic: Challenges and Insights from Covid-19*. Edward Elgar Publishing.

ONS (2020). Key workers reference tables.

Paez, A., Lopez, F. A., Menezes, T., Cavalcanti, R., and Pitta, M. G. d. R. (2020). A spatio-temporal analysis of the environmental correlates of covid-19 incidence in spain. *Geographical analysis*.

Roca, J. D. L. and Puga, D. (2016). Learning by Working in Big Cities. *The Review of Economic Studies*, 84(1):106–142.

Rodríguez-Pose, A. and Burlina, C. (2021). Institutions and the uneven geography of the first wave of the covid-19 pandemic. *Journal of Regional Science*.

Sá, F. (2020). Socioeconomic determinants of covid-19 infections and mortality: evidence from england and wales.

Schiavina, M., Freire, S., and MacManus, K. (2019). GHS population grid multitemporal (1975, 1990, 2000, 2015) R2019A. European Commission, Joint Research Centre (JRC).

Schiavina, M., Freire, S., Rosina, K., Ziemba, L., Marin Herrera, M., Craglia, M., Lavalle, C., Kemper, T., and Batista, F. (2020). ENACT-POP R2020A - ENACT 2011 Population Grid. European Commission, Joint Research Centre (JRC).

Thomas, L. J., Huang, P., Yin, F., Luo, X. I., Almquist, Z. W., Hipp, J. R., and Butts, C. T. (2020). Spatial heterogeneity can lead to substantial local variations in covid-19 timing and severity. *Proceedings of the National Academy of Sciences*, 117(39):24180–24187.

Travaglio, M., Yu, Y., Popovic, R., Selley, L., Leal, N. S., and Martins, L. M. (2021). Links between air pollution and COVID-19 in England. *Environmental Pollution*, 268:115859.

Wong, D. W. and Li, Y. (2020). Spreading of covid-19: Density matters. *Plos one*, 15(12):e0242398.

Wu, X., Nethery, R. C., Sabath, B. M., Braun, D., and Dominici, F. (2020). Exposure to air pollution and COVID-19 mortality in the United States. *MedRxiv*.

Appendix

Calculation of Residents and Workers Types

For each neighbourhood we observe the number of residents employed in each of 362 occupations[14]. We denote the count of residents in each occupation, denoted o_4, and neighbourhood i by N^r_{i,o_4}. To identify the number of jobs that likely would have continued to be done onsite throughout the first year of the pandemic, we use the classification from the Key Workers Reference Tables (ONS, 2020), which classifies jobs by occupation and industry as *key*, *KW=1*, or not *KW=0*[15]. From these tables we create a key work index for each of the 362 occupation codes by calculating the weighted average value of KW for each occupation code, where weighting is based on information from all Jan 2017-Jan 2020 waves of the UK Quarterly Labour Force Survey. The resulting occupation-specific index, $KW_{o_4} \in \{0, 1\}$, is then used to calculate the proportion of the residential population in a keywork job in each neighbourhood i. We combine this with the occupation-specific work-from-home index, $h_{o_4} \in \{0, 1\}$, from De Fraja et al. (2021). This index tells us the proportion of work in each occupation that can be done from home. Using this information we calculate the proportion of residents that are employed in key work occupations that require being onsite:

$$KW^r_i = \sum_{o_4} N^r_{i,o_4} \times KW_{o_4} \times (1 - h_{o_4}), \tag{A.1}$$

We also calculate the proportion of keywork jobs that are performed in each neighbourhood (workers may live in the same neighbourhood or elsewhere), $keyworkers^w_i{}_i$. For workers we observe 90 occupations[16]. We calculate $keyworkers^w_i{}_i$ using the same method as described above, only now we must aggregate the keywork index and work-from-home index to the three-digit SOC, which we denote as $K\hat{W}_{o_3} \in \{0, 1\}$ and $\hat{h}_{o_3} \in \{0, 1\}$. The proportion of keywork workers employed in each neighbourhood is calculated as:

$$KW^w_i{}_i = \sum_{o_3} N^w_{i,o_3} \times KW_{o_3} \times (1 - h_{o_3}). \tag{A.2}$$

where $keyworkers^w_i{}_i$ takes a value between 0 and 1 reflecting the amount of work done by all employees in MSOA i that requires being onsite and was not subject to lockdown restrictions. N^w_{i,o_3} denotes the number of jobs in occupation o_3 and N^w_i denotes total number of jobs, across all occupations, in MSOA i.

[14]Four-digit occupation codes as defined by UK Standardized Occupational Classification.

[15]Key worker information is reported for each four-digit SOC and four-digit SIC combination. There are 124,564 combinations in total, many of which contain no or very low actual employment in practice. More information available at the following link.

[16]Three-digit occupation codes as defined by UK Standardized Occupational Classification.

The proportion of homeworkers is calculated in a similar manner to key workers above. For jobs that can be done from home held by residents we calculate:

$$HW_i^r = \sum_{o_4} N_{i,o_4}^r \times (1 - KW_{o_4}) \times h_{o_4}, \tag{A.3}$$

and for jobs that can be done from home held by workers in the neighborhood we calculate:

$$HW_i^w = \sum_{o_3} N_{i,o_3}^w \times (1 - KW_{o_3}) \times h_{o_3}. \tag{A.4}$$

The unemployed residential population, $nonworkers_i^r$, is the total neighbourhood population minus the number of employed residents. The number of residents and workers in any other form of non-key jobs which cannot be done from home are calculated as the residual of these shares:

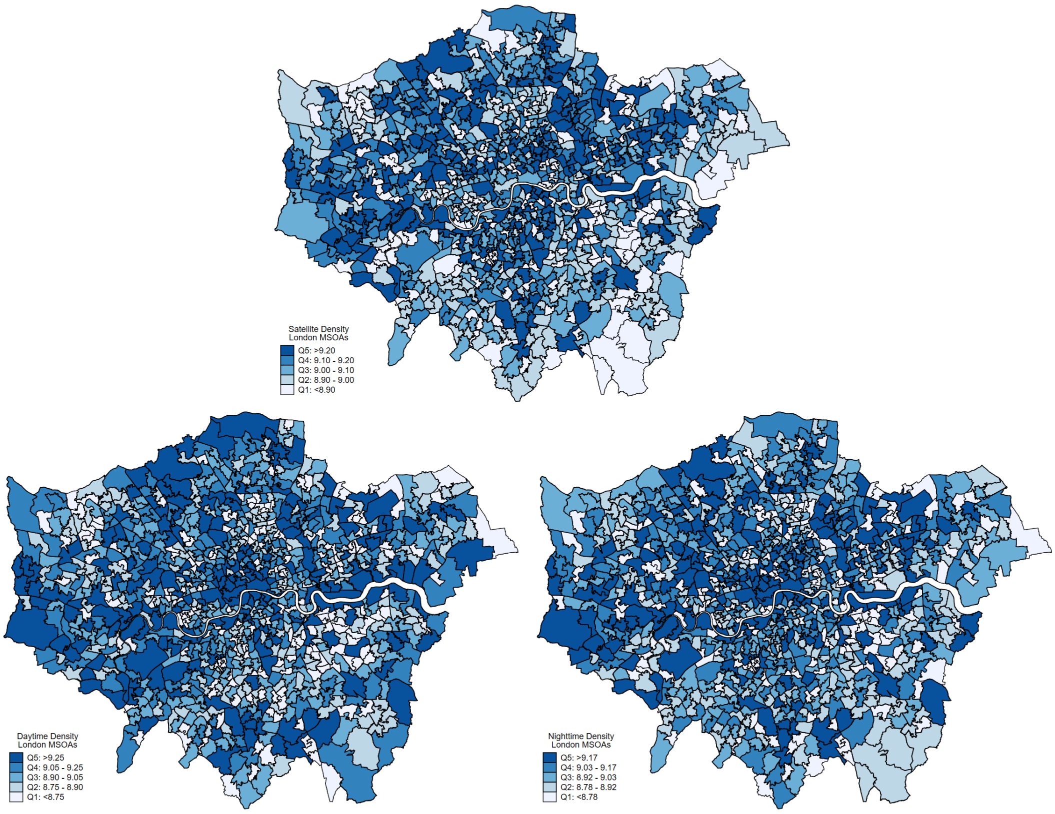
$$OW_i^r = N_i^r - NW_i^r - HW_i^r - KW_i^r, \tag{A.5}$$

and

$$OW_i^w = N_i^w - HW_i^w - KW_i^W. \tag{A.6}$$

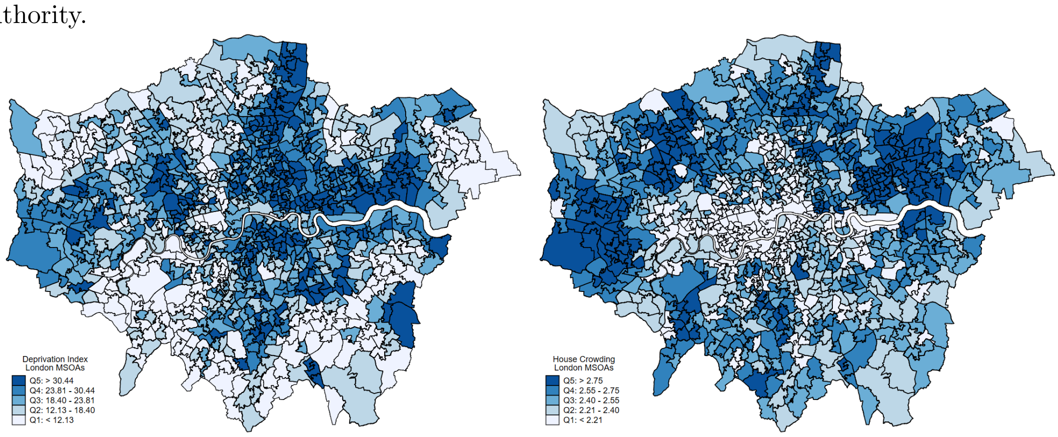
Additional analysis

Figure A1: Satellite, daytime and nighttime density across MSOAs within the Greater London Authority.



Notes: Elaboration based on GHS-POP and ENACT-POP data.

Figure A2: Deprivation and house crowding index across MSOAs within the Greater London Authority.



Notes: Elaboration based on ONS data for 2019.

Table A1: Selected occupations by allocation into work types

Keywork occupations		**Homework occupations**		**Other occupations**	
SOC Code	*Description*	*SOC Code*	*Description*	*SOC Code*	*Description*
1181	Health services and public health	1115	Chief executives	1221	Hotel and accommodation mngrs and
1211	Mngrs/Proprioters in agriculture	1116	Elected officers	2451	Librarians
1242	Residential care managment	1131	Financial mngrs and directors	2452	Archivists and curators
2211	Medical practitioners	1134	Advertising and public relations	3414	Dancers and choreographers
2213	Pharmacists	1135	Human resource mngrs	3415	Musicians
2215	Dental practitioners	1136	IT and telecom directors	3441	Sports players
2216	Veterinarians	1150	Financial institution mngrs	3442	Sports coaches and instructors
2217	Medical radiographers	1190	mngrs and directors in retail	3443	Fitness instructors
2218	Podiatrists	1226	Travel agency mngrs	3565	Inspectors of standards
2219	Health professionals	1255	Waste disposal and environmental	5112	Horticultural trades
2221	Physiotherapists	1259	Mngrs in other services	5114	Groundsmen and greenkeepers
2222	Occupational therapists	2129	Engineering professionals	5211	Smiths and forge workers
2223	Speech and language therapists	2133	IT specialist mngrs	5225	Air-conditioning
2231	Nurses	2136	Programmers and software	5232	Vehicle body repair
2232	Midwives	2137	Web design and development	5249	Electrical and electronic
2315	Primary and nursery education	2212	Psychologists	5250	Skilld metal, and electrical
2316	Special needs education	2311	Higher education teaching	5316	Glaziers and window fabricators
3213	Paramedics	2314	Secondary education teaching	5319	Construction and building trades
3217	Pharmaceutical technicians	2317	Snr professionals in education	5321	Plasterers
3218	Medical and dental technicians	2419	Legal professionals	5322	Floorers and wall tilers
4123	Bank and post office clerks	2423	Management consultants	5323	Painters and decorators
5111	Farmers	2426	Business and related research	5330	Construction and building trades
5235	Aircraft maintenance	2429	Business, research and admin	5411	Weavers and knitters
5231	Vehicle technicians/mechanics	2431	Architects	5413	Footwear and leather working
5431	Butchers	2432	Town planning officers	5414	Tailors and dressmakers
5432	Bakers and confectioners	2462	Quality assurance and regulatory	5435	Cooks
5433	Fishmongers	2471	Journalists, newspaper	5436	Catering and bar managers
6121	Nursery nurses and assistants	2472	Public relations professionals	5442	Furniture makers
6122	Childminders	3112	Electrical and electronics	5443	Florists
6123	Playworkers	3114	Building and civil engineering	5449	Other skilled trades
6131	Veterinary nurses	3116	Planning, process and production	6132	Pest control officers
6141	Nursing auxiliaries	3121	Architectural and town planning	6211	Sports and leisure assistants
6142	Ambulance staff	3131	IT operations technicians	6231	Housekeepers and related
6143	Dental nurses	3412	Authors, writers and translators	8112	Glass and ceramics process
6145	Care workers and home carers	3421	Graphic designers	8113	Textile process operatives
6146	Senior care workers	3533	Insurance underwriters	8119	Process operatives
6148	Undertakers and crematorium	3534	Finance and investment analysts	8121	Paper and wood machine operatives
6215	Rail travel assistants	3536	Importers and exporters	8125	Metal working machine operatives
7112	Retail cashiers	3537	Financial and accounting	8131	Assemblers (electrical)
7114	Pharmacy assistant	3538	Financial accounts mngrs	8132	Assemblers (vehicles)
8111	Food, drink and tobacco process	3542	Business sales executives	8214	Taxi and cab drivers
8126	Water and sewerage plant	3545	Sales accounts and development	8229	Mobile machine drivers
8143	Rail construction and maintenance	3562	Human resources	8239	Other drivers
8231	Train and tram drivers	4112	National gov. administrative	9112	Forestry workers
8234	Rail transport operatives	4121	Credit controllers	9132	Industrial cleaning process
9111	Farm workers	4132	Pensions and insurance clerks	9139	Elementary process plant
9211	Postal workers	4151	Sales administrators	9236	Vehicle valeters and cleaners
9235	Refuse and salvage	5245	IT engineers	9242	Parking and civil enforcement
9244	School crossing patrol	7113	Telephone salespersons	9272	Kitchen and catering assistants
9271	Hospital porters	7215	Market research interviewers	9273	Waiters and waitresses

Notes: Keywork occupations defined following the UK Government Key workers reference table. Homework occupations are defined following the methodology developed by Dingel and Neiman (2020) and De Fraja et al. (2021). Other occupations include all remaining non-essential onsite jobs not categorised in the other two typologies.

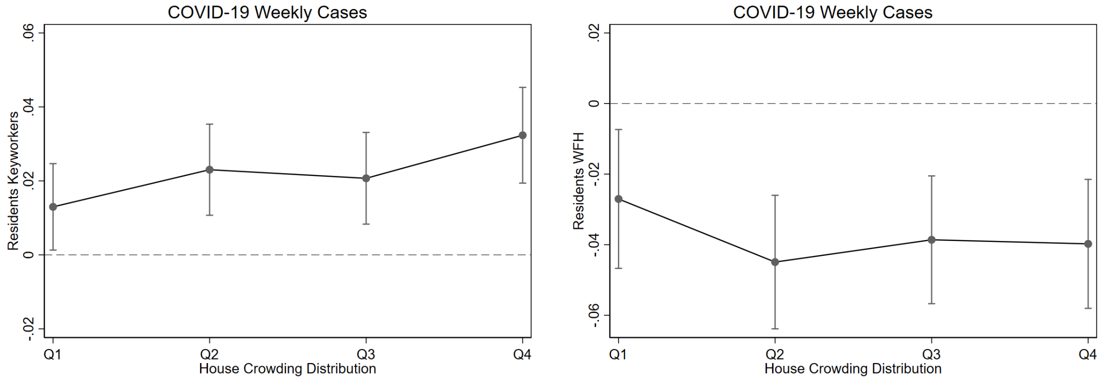
Table A2: Summary statistics for main Covid-19 and neighborhood labour structure variables in our estimation sample.

	mean(log)	mean(value)	sd(log)	sd(value)
Weekly Cases	1.237	3.4	1.381	4.0
KW_i^r	6.649	772.4	0.259	1.3
HW_i^r	7.265	1429.0	0.382	1.5
KW_i^w	6.352	573.5	0.691	2.0
HW_i^w	6.787	886.2	0.780	2.2
$HS-KW_i^r$	5.384	217.8	0.354	1.4
$MS-KW_i^r$	5.488	241.9	0.299	1.3
$LS-KW_i^r$	5.687	295.0	0.379	1.5
$HS-HW_i^r$	6.418	612.6	0.470	1.6
$MS-HW_i^r$	6.634	760.4	0.342	1.4
$LS-HW_i^r$	3.868	47.9	0.303	1.4
$HS-KW_i^w$	5.104	164.6	0.729	2.1
$MS-KW_i^w$	5.183	178.2	0.734	2.1
$LS-KW_i^w$	5.400	221.5	0.657	1.9
$HS-HW_i^w$	6.110	450.4	0.810	2.2
$MS-HW_i^w$	5.895	363.2	0.766	2.2
$LS-HW_i^w$	4.210	67.4	0.752	2.1
NW_i^r	8.384	4377.1	0.281	1.3

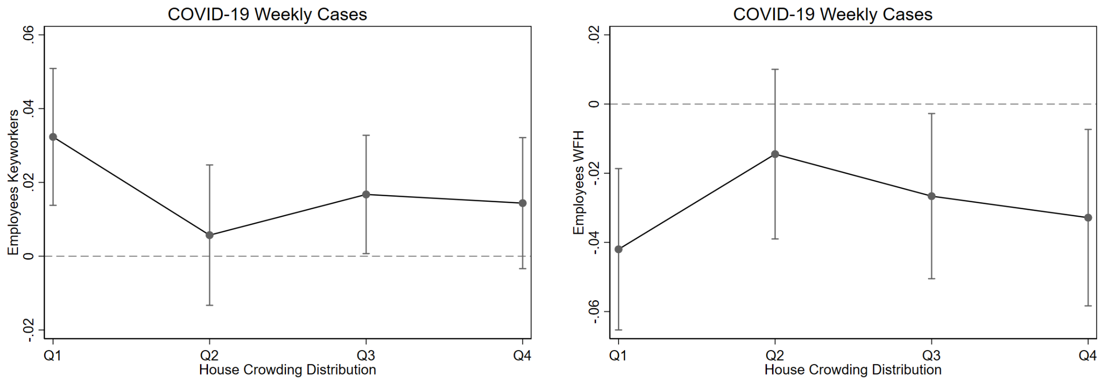
Notes: Mean and standard deviation reported both for logs and natural values.

Figure A3: Relationship between neighbourhood labour structure and COVID-19 weekly cases across the neighbourhood house crowding distribution.

a) Residents



b) Employees



Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood house crowding distribution reported from least (Q1) to most crowded (Q4) MSOAs. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Table A3: Relationship between population, employment density, neighborhood labour structure and COVID-19 weekly cases by MSOA - Rates.

	(1) Weekly Cases	(2) Weekly Cases	(3) Weekly Cases	(4) Weekly Cases
Satellite Density	0.014***			
	(3.40)			
Daytime Density		-0.001		
		(-0.41)		
Nighttime Density		0.007**		
		(3.08)		
Population Density			0.016***	0.007*
			(5.14)	(2.42)
Employment Density			-0.004	-0.005
			(-1.12)	(-1.32)
Residents Keyworkers				-0.012***
				(-3.64)
Residents WFH				-0.063***
				(-16.27)
Employees Keyworkers				0.008***
				(4.66)
Employees WFH				-0.002
				(-0.98)
Residents Not Employed				0.001
				(0.38)
LAD FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y
Observations	441285	441285	441285	441285
R^2	0.834	0.834	0.834	0.835

Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Table A4: Relationship between population, employment density, neighborhood labour structure and COVID-19 weekly cases by MSOA - Pre-vaccination 2020 only.

	(1) Weekly Cases	(2) Weekly Cases	(3) Weekly Cases	(4) Weekly Cases
Satellite Density	0.014**			
	(3.23)			
Daytime Density		-0.002		
		(-0.83)		
Nighttime Density		0.007**		
		(2.66)		
Population Density			0.004	0.004
			(1.1)	(1.22)
Employment Density			0.023***	0.022***
			(5.67)	(-5.3)
Residents Keyworkers				0.010*
				(2.44)
Residents WFH				0.003
				(0.44)
Employees Keyworkers				0.022***
				(4.4)
Employees WFH				-0.018*
				(-2.08)
Residents Not Employed				0.002
				(0.22)
LAD FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y
Observations	298716	298716	298716	298716
R^2	0.825	0.825	0.826	0.826

Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Table A5: Relationship between population, employment density, neighborhood labour structure and COVID-19 cumulative cases by MSOA.

	(1) Cum. Cases	(2) Cum. Cases	(3) Cum. Cases	(4) Cum. Cases
Satellite Density	0.069***			
	(4.71)			
Daytime Density		-0.001		
		(-0.11)		
Nighttime Density		0.027**		
		(2.96)		
Population Density			0.093***	0.083***
			(5.96)	(5.15)
Employment Density			0.015	0.022
			(0.89)	(1.32)
Residents Keyworkers				0.126***
				(7.59)
Residents WFH				-0.147***
				(-5.60)
Employees Keyworkers				0.024
				(1.43)
Employees WFH				-0.098***
				(-3.65)
Residents Not Employed				0.036
				(0.90)
LAD FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y
Observations	6789	6789	6789	6789
R^2	0.882	0.882	0.885	0.893

Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Table A6: Relationship between population, employment density, neighborhood labour structure and COVID-19 monthly deaths by MSOA.

	(1) Monthly Deaths	(2) Monthly Deaths	(3) Monthly Deaths	(4) Monthly Deaths
Satellite Density	0.021**			
	(2.85)			
Daytime Density		0.003		
		(-0.53)		
Nighttime Density		-0.007		
		(-1.46)		
Population Density			0.032***	0.032***
			(4.76)	(4.67)
Employment Density			0.020*	0.023**
			(2.5)	(2.86)
Residents Keyworkers				0.036***
				(5.2)
Residents WFH				-0.008
				(-0.69)
Employees Keyworkers				0.003
				(0.31)
Employees WFH				-0.037*
				(-2.38)
Residents Not Employed				0.032
				(1.79)
LAD FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y
Observations	95046	95046	95046	95046
R^2	0.606	0.605	0.606	0.607

Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Table A7: Relationship between population, employment density, neighborhood labour structure and monthly excess mortality by MSOA in 2020.

	(1) Ex. Mortality	(2) Ex. Mortality	(3) Ex. Mortality	(4) Ex. Mortality
Satellite Density	0.032*			
	(1.86)			
Daytime Density		0.01		
		(0.82)		
Nighttime Density		0.001		
		(0.11)		
Population Density			-0.012	-0.014
			(-0.74)	(-0.86)
Employment Density			0.004	0.007
			(0.33)	(0.48)
Residents Keyworkers				-0.021
				(-0.93)
Residents WFH				-0.075**
				(-2.44)
Employees Keyworkers				-0.028
				(-1.23)
Employees WFH				-0.028
				(-0.66)
Residents Not Employed				-0.108
				(-1.65)
MSOA FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y
Observations	81468	81468	81468	81468
R^2	0.329	0.329	0.329	0.329

Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

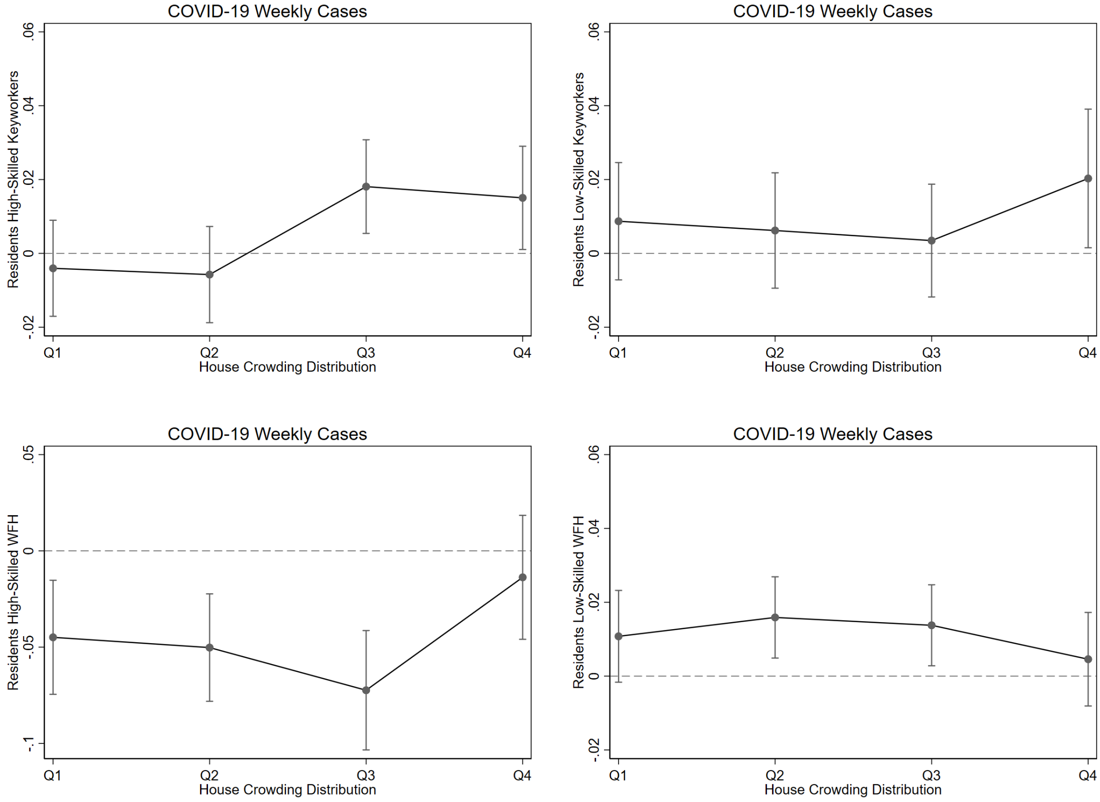
Table A8: Relationship between population, employment density, neighborhood labour structure and COVID-19 weekly cases by MSOA in large and small TTWAs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Small TTWAs				**Large TTWAs**		
	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases
Satellite Density	-0.004				0.016**			
	(-0.77)				(3.29)			
Daytime Density		-0.004				-0.007*		
		(-1.29)				(-2.24)		
Nighttime Density		0.007*				0.011**		
		(2.13)				(3.19)		
Population Density			-0.004	-0.008			0.014***	0.013**
			(-0.87)	(-1.57)			(3.50)	(3.08)
Employment Density			0.016***	0.017***			0.016**	0.017**
			(3.44)	(3.36)			(2.95)	(3.23)
Residents Keyworkers				0.025***				0.017***
				(4.71)				(3.69)
Residents WFH				-0.021**				-0.026**
				(-2.70)				(-2.89)
Employees Keyworkers				0.012				0.006
				(1.86)				(0.98)
Employees WFH				-0.032**				-0.019
				(-3.29)				(-1.68)
Residents Not Employed				0.026*				-0.040**
				(2.01)				(-3.13)
LAD FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	215995	215995	215995	215995	223925	223925	223925	223925
R^2	0.810	0.810	0.811	0.811	0.831	0.831	0.831	0.831

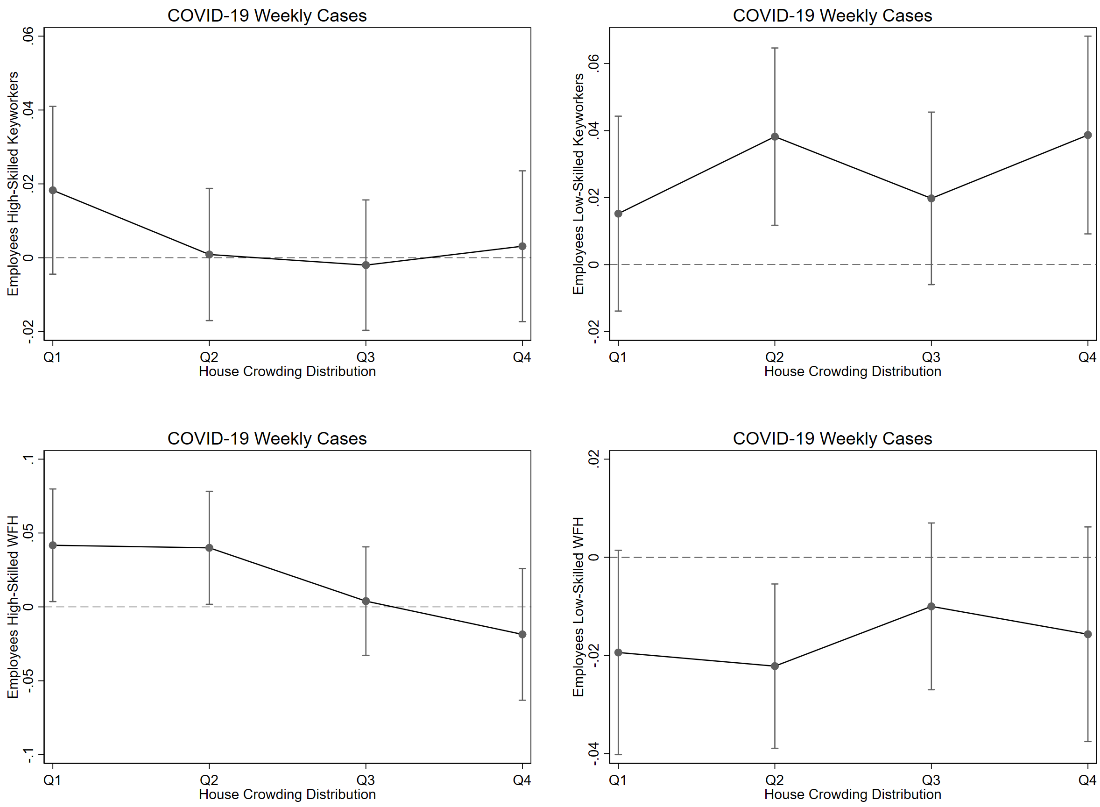
Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Figure A4: Relationship between neighbourhood skilled labour structure and COVID-19 weekly cases across the neighbourhood house crowding distribution.

a) Residents



b) Employees



Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood deprivation distribution reported from least deprive (Q1) to most deprived (Q4) MSOAs. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

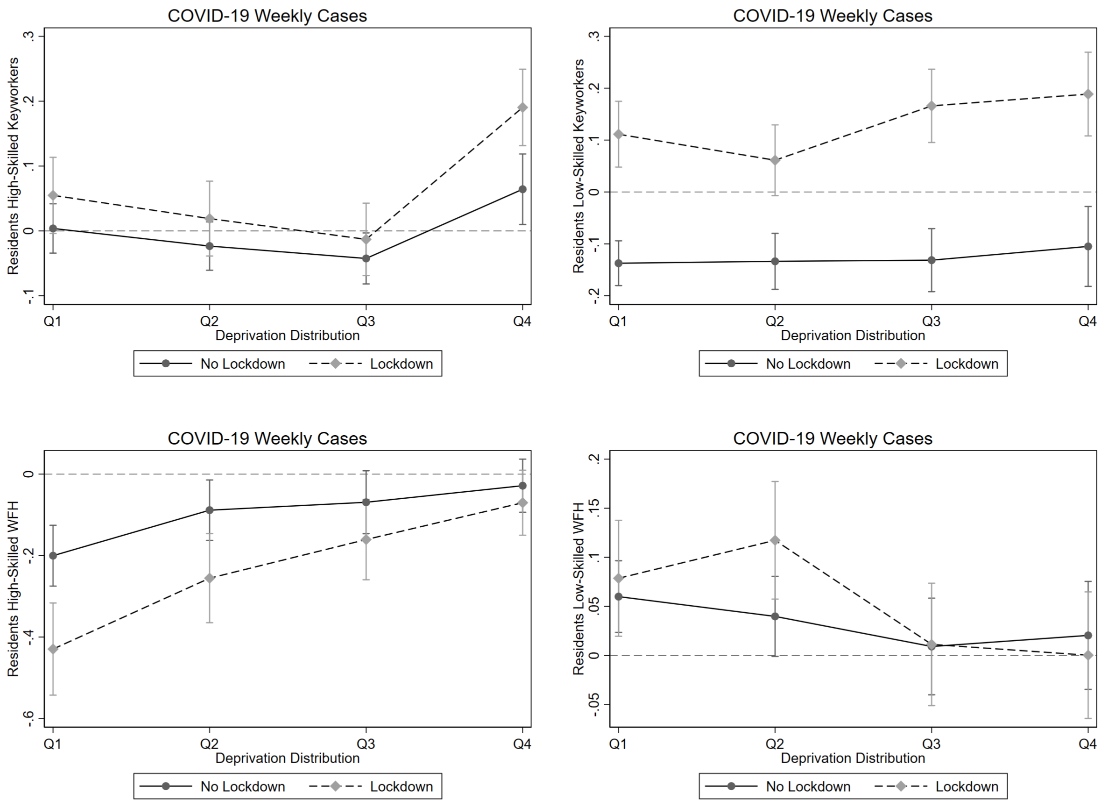
Table A9: Relationship between population, employment density, neighborhood skilled labour structure and COVID-19 weekly cases by MSOA during lockdown periods.

	(1) No Lockdown Weekly Cases	(2) Lockdown Weekly Cases	(3) No Lockdown Weekly Cases	(4) Lockdown Weekly Cases
Residents Keyworkers	-0.027***	0.086***		
	(-5.90)	(15.90)		
Residents WFH	-0.007	-0.051***		
	(-0.85)	(-5.49)		
Employees Keyworkers	0.019***	0.003		
	(3.46)	(0.47)		
Employees WFH	-0.008	-0.046***		
	(-0.82)	(-4.23)		
Residents High-Skilled KEY			-0.002	0.017***
			(-0.65)	(3.71)
Residents Medium-Skilled KEY			-0.010**	0.038***
			(-2.70)	(8.46)
Residents Low-Skilled KEY			-0.028***	0.054***
			(-5.23)	(8.74)
Residents High-Skilled WFH			-0.021*	-0.049***
			(-2.49)	(-4.62)
Residents Medium-Skilled WFH			0.002	0.014
			(0.29)	(1.38)
Residents Low-Skilled WFH			0.006	0.011**
			(1.78)	(2.67)
Employees High-Skilled KEY			-0.002	0.017**
			(-0.44)	(2.85)
Employees Medium-Skilled KEY			0.012**	-0.010
			(2.65)	(-1.73)
Employees Low-Skilled KEY			0.006	0.040***
			(0.78)	(3.86)
Employees High-Skilled WFH			-0.003	0.034*
			(-0.29)	(2.48)
Employees Medium-Skilled WFH			-0.003	-0.047***
			(-0.33)	(-4.27)
Employees Low-Skilled WFH			-0.008	-0.024***
			(-1.77)	(-4.20)
LAD FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y
Observations	264771	176514	264771	176514
R^2	0.819	0.783	0.819	0.783

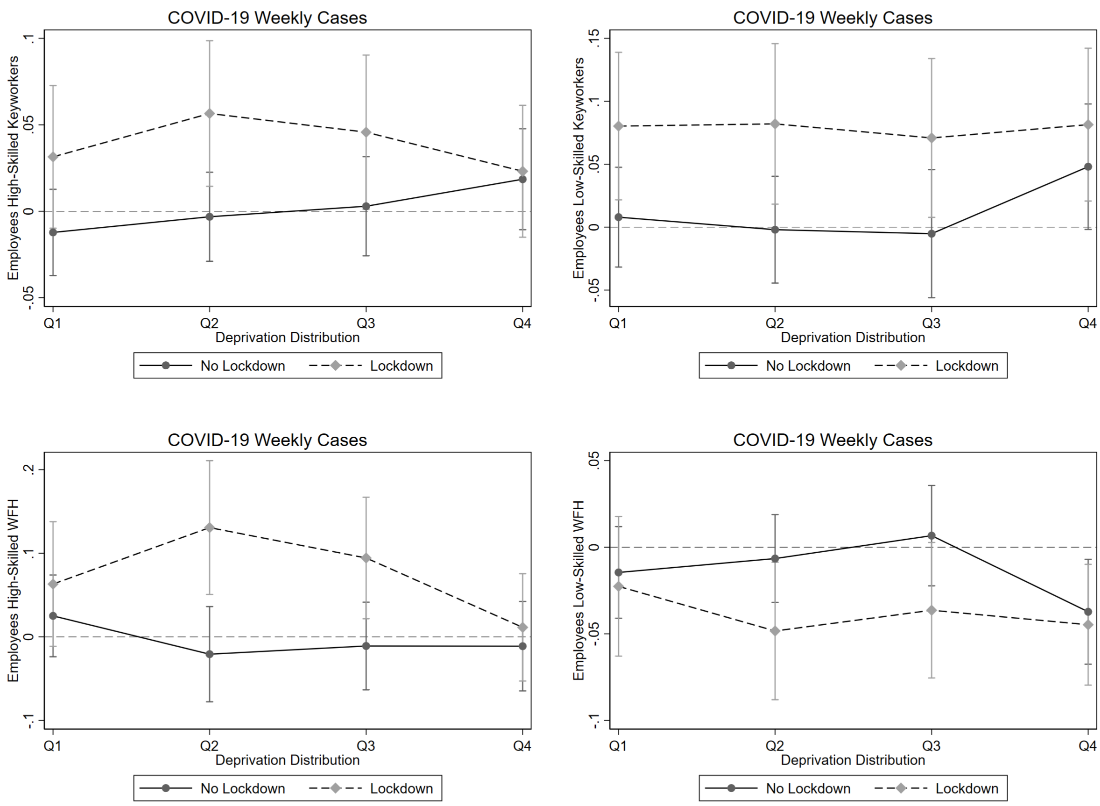
Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Lockdown periods considered are March-May 2020, November 2020, and January-April 2021. Control variables included: population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, IMD score, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.

Figure A5: Relationship between neighbourhood skilled labour structure and COVID-19 weekly cases across the neighbourhood deprivation distribution during lockdown periods.

a) Residents



b) Employees



Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood deprivation distribution reported from least deprive (Q1) to most deprived (Q4) MSOAs. Lockdown periods considered are March-May 2020, November 2020, and January-April 2021. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents, log-MSOA workers, population per residential property, PM 2.5 pollution, log-weighted cases for local authority, log number of carebeds in the MSOA.