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How important is neighbourhood labour structure in the spread of COVID-19? Within-city evidence from England

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Abstract

In this paper we estimate the importance of local labour structure in the spread of COVID-19 during the first year of the pandemic. We build a unique data set across 6,700 neighbourhoods in England that allows us to distinguish between people living (residents) and people working (workers) in a neighbourhood, and to differentiate between jobs that can be done from home (homeworkers), jobs that likely continued on-site (keyworkers), and non-essential on-site jobs. We use these data to study the relationship between the within-city variation in neighbourhood population/employment structures and the within-city variation in COVID-19 spread. Neighbourhood labour structure is important, explaining approximately 9.5% of the within-city variation over-and-above population density and other confounders. Holding residential population constant, 50 more residents working from home decreases neighbourhood cases by almost one-third relative to the mean; having 50 more residents in keywork jobs increases neighbourhood cases by almost two-thirds. We find the magnitude of these results varies by neighbourhood deprivation levels. In high-deprivation neighbourhoods, the positive effect of keyworkers on cases is larger, while the protective effect of homeworkers is lower than in more affluent areas. We speculate on how the various types of occupations within these job categories drive the differences across neighbourhoods. These findings point to important asymmetries in the social justice of the policy response to COVID-19, providing useful insights for the design of future economic policies and public health strategies during the endemic phase of the disease.

Keywords: Urban Density, Local Labour Market, Public Health Policy.

JEL Classification: H12, I18, R12.

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1 Introduction

From the outset of the COVID-19 outbreak, its spatial heterogeneity has been a striking feature. Several studies have shown how this variation reflects differences in socio-economic characteristics across locations, including income and age distribution, and the quality of healthcare and institutions (Carozzi et al., 2020; Desmet and Wacziarg, 2021; Rodríguez-Pose and Burlina, 2021; McCann et al., 2021). Urban density and population distribution have received particular attention in previous analysis due to the role of physical proximity as a key channel for the transmission of the SARS-CoV-2 virus (CDC, 2020; Stadnytskyi et al., 2020; WHO, 2020). However, notwithstanding the number of studies stressing the relationship between population density and viral contagion (Wong and Li, 2020; Allcott et al., 2020; Desmet and Wacziarg, 2021; Almagro and Orane-Hutchinson, 2020; Carozzi et al., 2020; Ascani et al., 2021; Armillei and Filippucci, 2020; McCann et al., 2021), there is still limited evidence about the underlying mechanisms through which local economic activity affects the viral spread.

In this paper, we contribute to the literature on spatial determinants of COVID-19 diffusion by looking at the role played by neighbourhood labour structure in the spread of COVID-19. Specifically, we investigate how much of the observed variation in viral spread within an urban area can be explained by the residential and employment distribution of the labour force. We explicitly examine three important margins not previously studied. First, we distinguish between the concentration of people who live in a neighbourhood (*residents*), and those who work there (*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 to be done on-site (*keyworkers*), and non-essential on-site jobs that likely experienced a pause during periods of public health restrictions (*otherworkers*). Finally, we evidence heterogeneous effects for each of these groups across occupation skill intensity and levels of neighbourhood deprivation.

Our analysis rests on a novel dataset that includes information on the spread of COVID-19 reported cases in the first year of the pandemic. We merge these data with detailed information on the population and labour market composition of 6,700 neighbourhoods across England.[1] These data have the important feature of offering neighbourhood-level information on the employment structure and residential population by occupation[2], allowing us to exploit within-city variation in

[1] Neighbourhoods are defined using the ONS Middle Super Output Area (MSOA) nomenclature reflecting on average 7,000 residents (3,000 residential buildings).

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

COVID-19 cases, residents, and employment. We add to these data information from an official list, published during the early stages of the pandemic, of jobs that were designated by the UK Government as *keywork*[3]. Over the lockdown periods that we examine, only keyworkers were allowed to continue working on-site. Following Dingel and Neiman (2020) and De Fraja et al. (2021), we combine these data with information reflecting occupations that can be done from home to decompose the pre-pandemic local labour structure of workers and residents for each neighbourhood according to these important margins of employment.

We document four important results. First, the density of both residents and workers in a neighbourhood is important. A one percent increase in the density of people who work in a neighbourhood is associated with a statistically significant increase of 0.016 percent in reported weekly cases; this is almost twice the magnitude of the corresponding elasticity for residential population density. This is particularly interesting when we consider that a recorded COVID-19 case corresponds to the infected person's neighbourhood of residence. Second, neighbourhood labour structure is important, explaining approximately 9.5% of the within-city variation over and above population density and other confounders. Holding residential population constant, having 50 more residents working from home (WFH) decreases reported cases in a neighbourhood by almost one-third relative to the mean. In contrast, having 50 more residents in keywork jobs increases neighbourhood cases by almost two-thirds. Similar results are found for the occupation composition of people working in a neighbourhood, although these are smaller in magnitude. Third, the importance of the occupational composition of residents, as opposed to workers, to the spread of COVID-19 varies by neighbourhood deprivation. Keyworkers in high-deprivation neighbourhoods have a particularly strong positive association with COVID-19 reported cases, while working from home (WFH) in affluent areas significantly limits the viral spread. We speculate on the mechanisms driving this by looking at within-household house crowding and by examining in detail the skill intensity differences of occupations across the neighbourhood deprivation distribution. Fourth, we find that the identified relationships are particularly important during lockdown periods. This has implications for the social justice of public health policies. Lock-down policies come at higher cost in neighbourhoods that are more deprived because, compared to low-deprivation neighbourhoods, these are home to fewer workers with jobs that can be done from home; such policies also produce less of a benefit in terms of slowing the spread of the virus in high-deprivation neighbourhoods. Our findings show that labour composition is essential to understand such within-city differences. These results are shown to be robust to different measures of density and of COVID-19 spread,

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

and to further validity tests.

Our contribution to the existing literature and evidence base is threefold. First, in distinguishing between the resident and worker populations of neighbourhoods, we are able to unpack the channels through which urban density facilitates the spread of the virus across neighbourhoods through social and economic interactions. Thus, we contribute to the emerging literature documenting the critical role played by industrial and employment density in spreading the virus (Almagro and Orane-Hutchinson, 2020; Ascani et al., 2021; Di Porto et al., 2022) by providing first evidence of the differential impact of the local labour structure on COVID-19 transmission with respect to where people live and where they work has so far received limited attention.

Second, we extend previous studies conducted at broad levels of spatial aggregation, where data is considered at provincial or regional level, by offering country-wide evidence about within-city variation in COVID-19 morbidity. Similarly, our granular data on local labour structure allow us to expand the limited evidence on the impact of essential workers and sectors in the spread of COVID-19 infections (Brandily et al., 2021; Di Porto et al., 2022) not just differentiating between residential and workplace locations, but also exploring differential effects across levels of occupation skill intensity and neighbourhood deprivation.

Finally, we investigate the heterogeneous role of local labour composition in the spread of COVID-19 across the socio-economic structure of neighbourhoods during different phases of the pandemic. Accordingly, we contribute to the literature on the effects of lockdowns and stay-at-home orders (Alvarez et al., 2020; Acemoglu et al., 2020; Glaeser et al., 2020; Bourdin et al., 2021) by documenting the effectiveness of lockdowns as public health measures with respect to the spatial heterogeneity in the distribution of occupation types and level of housing deprivation across neighbourhoods. These elements are particularly relevant to evaluate possible asymmetries in the social justice of lockdowns and other public health measures, especially for the most deprived neighbourhoods in the country.

As governments remove public health restrictions transitioning to an endemic phase, it is necessary to disentangle the black box of density to identify more precisely the relationship between proximity and viral transmission, as economies make adjustments to live with the virus. (Lewis, 2021; Phillips, 2021). Our findings offer a more nuanced comprehension of where and how contagion takes place, whether this be at home or at the place of work, and through which type of jobs. As outbreaks slowly recede and COVID-19 becomes endemic, understanding these differences is increasingly important for the effective design of policies that can address the impact of the COVID-19 pandemic on productivity (McCann and Vorley, 2021), jobs and income loss inequalities (Adams-Prassl et al., 2020; Stantcheva, 2022), mental health (Adams-Prassl et al., 2022), and the shift towards working from home (Bartik et al., 2020; De Fraja et al., 2021). In particular, by unpacking the heterogeneous impact of the virus within local labour market structures and across neighbourhood deprivation, our results can inform the implementation of public transfers and other support schemes for the most affected workers and households (Basso et al., 2021; Aspachs et al., 2022).

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, and outline the main policy interventions adopted in England to curb transmission. Section 3 describes the data used. Section 4 discusses the research design for the empirical analysis. Results are presented in Section 5. Section 6 concludes the paper and discusses its policy implications.

2 Literature Review

2.1 Urban Density and COVID-19

Following the outbreak of the COVID-19 pandemic, a growing literature has rapidly emerged on the spatial variation in the incidence rates of viral infections. In particular, significant attention has been given 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 when 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, the transmission mechanisms of the SARS-CoV-2 virus mean that density nevertheless potentially retains a critical role in the diffusion of COVID-19. 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 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 that population density exerts an effect 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 affected the timing of the outbreak, but no evidence that population density is positively associated with time-adjusted COVID-19 cases. They suggest that 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 that higher spatial resolution is to be preferred, because COVID-19 transmission is more effectively defined at sub-county geographical scales. In line with this, Desmet and Wacziarg (2021) draw on county level data on COVID-19 reported cases and deaths in the US in their exploration of the role of density; they find limited evidence that population density plays a role in reported cases, but that it has a positive effect on reported deaths. However, they show that effective density - calculated as the average density that a random individual of a county experiences in the square kilometer around them - 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 lower 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 when looking at selected cities at ZIP level (Almagro and Orane-Hutchinson, 2020; Guha et al., 2020). Similar results have been found from 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 underlined by the consistent effect of house crowding proxies - that matters. Thus, COVID-19 cases result from highly localised interactions; these are not simply a function of being in a large urban area as opposed to a smaller city environment, but rather driven from the types of social interactions that are occurring.

2.2 Local Economic Activity and COVID-19

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, which they define as an employment-weighted Herfindahl–Hirschman index. They find evidence suggesting that larger employment in geographically concentrated industries positively impacts COVID-19 cases. This effect seems to be driven by employment in manufacturing. Thus, they suggest that 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 the 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, most notably 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). Finally, recent contributions have explored the impact of essential workers and essential occupations, evidencing a positive effect on the spread of COVID-1 ((Brandily et al., 2021; Di Porto et al., 2022)).

2.3 The Role of Public Health Policies

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 similar public health measures in the UK (Alvarez et al., 2020; Acemoglu et al., 2020; Courtemanche et al., 2020). In the period between March 2020 and April 2021, England went 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 out 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 to first lockdown level in November. 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 measure started to relax from March 2021.

As shown by Glaeser et al. (2020) who explored zip-code level data for selected cities in the US, restrictions on mobility may lead to a significant reduction in COVID-19 cases, with total cases per capita decreasing up to 30% for every 10 percentage point fall in mobility. Similarly, the lockdown strategy introduced in Italy at the beginning of the first wave has been shown to have reduced the spread of the virus away from provinces that were first hit (Bourdin et al., 2021). After the onset of the pandemic, the role played by density was not shaped solely by policy. Indeed, the changes in mobility that reduced transmission rates were also 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, 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 that the positive effect of the share of employment in essential and non-essential professional and service occupations first 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, indicating that lockdowns reduce risk in public places or the workplace, but only mitigate transmission in occupations that have to remain in operation during 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.

2.4 Evidence Base Summary

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 the density of where people live that may lead to higher COVID-19 incidence, particularly given the way in which cases and deaths are reported. In the same way, household size and the level of deprivation experienced may result in an higher incidence of COVID-19, because of a higher density of people in each home leading to higher levels of intra-household contagion.

That being said, it is the nature of the social and economic interactions within the neighbourhoods that will help us to understand how viral diseases spread across neighbourhoods. These are likely reflected in the occupational structures of residents and workers in a neighbourhood. While most workers moved to WFH solutions during the pandemic, keyworkers who still operated on-site and engaged in their usual activities would be expected to achieve much lower levels of social distancing, even with the introduction of public health recommendations in their workplaces. Thus, for the same level of density, we would expect areas with a higher proportion of resident and employed keyworkers to be characterised by higher levels of COVID-19 incidence. Furthermore, in such a case, very similar dynamics should be expected with regard to the roles played by household density and deprivation. These would likely be exacerbated in places with more keyworkers, as such workers rarely had the option of maintaining their income level while working from home; they would be more exposed to contagion during their work, which they would then spread once they were back at home.

Finally, previous evidence suggests these effects to be significantly affected by lockdown policies. In the absence of lockdowns, the link between keyworkers density and COVID-19 can be expected to be more marked. Lockdowns are likely to reduce transmission through keyworkers because they will come into contact with a much smaller part of the population. 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 lower population density, but their effect may be less strong in more densely populated areas with high levels of house crowding, where social interactions and mixing of households are more likely to remain elevated.

3 Data

Our analysis is based on several datasets linked together at the neighbourhood level. We define a neighbourhood as a Middle Super Output Area (MSOA), using the geographic hierarchy nomenclature of 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 (around 3000 households). Towns and cities are defined as Local Authority Districts (LAD), which are the geographic areas governed by a single municipal council. Each LAD is made up of a number of MSOAs, and every MSOA comes under just one LAD. Importantly, all public health measures in the UK during the pandemic were either administered at the national level or at 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 MSOA level are provided by the Office of National Statistics (ONS). The number of COVID-19 reported cases in each MSOA is registered weekly, while COVID-19 related deaths are reported monthly for each neighbourhood.

[FIGURE 1 HERE]

As it is evident in Figure 1, there are stark differences in the numbers of COVID-19 cases and deaths across neighbourhoods in London, even between those that are adjacent or fall within the same LAD. For instance, we can see that while COVID-19 reported cases seem to be mostly clustered in the east and west of the Greater London Authority, i.e. the most deprived areas of the city, COVID-related deaths are much more randomly distributed, even extending to the more affluent neighbourhoods to the south of the city.

3.2 Urban Density

We start by calculating urban density in a conventional way, using the population and employment counts provided by the 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 population 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^r is the residential population in LSOA j and N_i^r is the residential population in MSOA i. $Pop.Den_i$ 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:

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

From these data we also derive an overall measure of urban density, which takes into account the sum of residents and employees in a given neighbourhood divided by the MSOA land area, using superscript w to denote *workers* as opposed to residents:

$$Urb.Den_i = \frac{N_i^r + N_i^w}{Area_i}, \tag{3}$$

Figure 2 reports the different distributions 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 sheds light on how these measures might not be effectively capturing 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-19 cases and deaths, which are mainly clustered in suburban and peripheral areas, and of population and employment density, which are mostly concentrated in city centres. This indicates the need to consider using different measures of the spatial distribution of urban density that can take into consideration those characteristics of the residential and worker populations that are more related to 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 (r) and workers (w) in each neighbourhood (i). 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:[4]

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

$$N_i^r = NW_i^r + KW_i^r + HW_i^r + OW_i^r,$$
$$N_i^w = KW_i^w + HW_i^w + OW_i^w.$$

The variable KW measures the number of people in an occupation denoted as *keywork*, such as hospital staff, primary educators, critical retail staff, and public transport workers; these workers likely continued working on-site throughout the pandemic lock-downs. In contrast, HW is the number of people who would have been able to do a significant portion of their job from home (*homeworkers*). Finally, all other workers, OW, denotes the number of people employed in non-essential work that was unlikely to be able to be done from home. This final category would include, for instance, many workers in retail and hospitality. In addition, NW_i^r is the number of residents in the neighbourhood who do not work, including children and retirees. Of course, we only observe this group for the residential population, not the working population.[5]

Using four-digit occupation classifications (SOC), we define occupations as able to be done from home by following the classification introduced in Dingel and Neiman (2020) and adapted by De Fraja et al. (2021) to the UK's occupation classification. This classification assigns each occupation an index value reflecting the proportion of the job that can be done from home. An occupation that cannot be done from home is defined as *keywork* if is identified as such by the nationally published Key Work Reference Tables (ONS, 2020); these identify the occupations that were legally allowed to be carried out outside of the house during the national lockdowns. In the supplementary Appendix, we provide details of the occupations assigned to each group, as well as

[5]Using this disaggregation method we might fail to identify the role of non-resident non-workers moving to a neighbourhood for school, leisure, or other activities. This should not be a significant concern, as we do control for the economic activity of the neighbourhood, which could proxy for leisure activity. Furthermore, school catchment areas mean that pupils tend to go to schools within their own neighbourhood. However, to better control for this, and also to provide robustness tests for the traditional urban density measures, we adopt the novel approaches seen in the urban economics literature (Henderson et al., 2019; Roca and Puga, 2016), and draw on satellite imagery data that allow for a finer level of granularity, filling the gaps in the more conventional datasets. We first use data from the GHS-POP spatial raster dataset on the distribution of people per 1 square kilometre 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. As an alternative, we also use LandScan data on the global population distribution at approximately 1 square kilometre spatial resolution for 2019 to check consistency (for more information regarding the LandScan data please refer to `https://landscan.ornl.gov/`). In addition, we use data from the ENACT-POP spatial raster dataset that captures seasonal nighttime and daytime changes in the number of people per squared kilometer in 2011 (Schiavina et al., 2020). 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 for purposes of 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 (for more information regarding the GHS-POP and the ENACT-POP data please refer to `https://ghsl.jrc.ec.europa.eu/datasets.php`). We transform the satellite data at the MSOA level by populating the MSOA polygons with data from the 1 kilometre squared raster layer, taking into account the proportion of the raster cell that each polygon covers. We find that population density is quite different across neighbourhoods at daytime and nighttime; population is clustered in city centres neighbourhoods during the day, but more densely located in suburban areas at night (Figure A1 in the Appendix). This highlights the importance of disentangling where people live from where they work, especially when studying the relevance of social interactions within and between households in an effort to explain the spread of viral diseases.

a table of representative jobs for each group.

[FIGURE 3 HERE]

Figure 3 supplements Figure 2 by showing a much more nuanced distribution of where *key-workers* or people able to work from home live and where they work across neighbourhoods in the Greater London Authority. In particular, we notice that the share of resident *keyworkers* is particularly high in neighbourhoods outside of the city centre, especially in the east side of the metropolitan area, which is also characterised by higher levels of economic deprivation. Interestingly, this seems to correlate significantly with the spatial incidence of COVID-19 cases previously shown in Figure 1. This is in strong contrast to the distribution of 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, in that we cannot identify 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 neighbourhoods that might explain the spatial spread of the virus within cities. First, we obtain further information on each neighbourhood's resident population from the ONS Nomis dataset. We have data on the proportion 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 neighbourhood socio-economic characteristics. We measure house crowding, calculated as the number of people per square metre of residential buildings, for which we use 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.[6] The level of particulate matter (PM 2.5), proxying for pollution, is measured using data from the Department for Environment, Food & Rural Affairs (DEFRA). Finally, we include information collected by the National Health Service (NHS) on the number of care beds available in each neighbourhood.

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

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:

$$COVID_{it} = \alpha_1 Density_{it} + X_i'\Gamma + \lambda_t + \theta_r + \gamma_{r,t} + e_{it}, \tag{4}$$

The dependent variable $COVID_{it}$ reflects the logged number of COVID-19 reported cases plus one for week (t) cases in each neighbourhood i. We mainly focus on cases, given that this is the aspect of COVID-19 infection that is most related to the labour market, in that it disrupts the usual functioning of the economy through self-isolation, sick leave, and absenteeism. Therefore, by focusing on COVID-19 cases we aim to understand which groups of workers across urban neighbourhoods would need particular attention to minimise the negative effect on the economy as the virus becomes endemic.[7] The primary independent variable of interest, $Density_{it}$ represents the different measures of density for neighbourhood i. We start by considering the overall measure of urban density ($Urbden_i$), before distinguishing between its two components, population ($Popden_i$) and employment counts per square kilometre ($Empden_i$). Finally, we also use monthly daytime and nighttime satellite imagery data for robustness, as previously defined in the data section.

We include controls for a number of neighbourhood characteristics in X_i, including log-population and log-employment counts, the proportion of residents under 18 years old, proportion 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 the spatial lags of the number

[7]Focusing on weekly reported cases could potentially generate two types of bias when trying to infer differences in actual cases: first, a measurement error when reported cases significantly differ from actual COVID-19 cases, and secondly omitted variable bias where the likelihood of residents and workers in different occupations being tested varies across neighbourhoods. We address these potential sources of estimation bias in several ways. First, given that COVID-19 tests in the UK are reported at the place of residence, we deem that this issue should not affect the estimates for the population of workers in a neighbourhood, as the largest majority would live, and report testing, in a different area. Second, while testing capacity was scarcer and mostly targeted at keyworkers during the first lockdown period (March-June 2020), testing capacity significantly increased later on, with a nationwide campaign of free testing kits for all citizens irrespective of occupation or location promoted by the National Health Service. Unfortunately, data on testing at such granular level are not available. However, our dynamic analysis in Figure 4 provides reassurance about the validity of our results by showing how our estimates remain statistically significant in the later phases of the pandemic, when testing was fully rolled-out and the impact of measurement and omitted variable biases should be limited. In addition, the dynamic analysis also precisely estimates the phase between lockdowns, when non-essential on-site jobs resumed and workers tested positive in higher number than the keyworkers and homeworkers because they were more exposed to social interactions. The results are also consistent when using as an outcome variable the cumulative number of COVID-19 cases in Table A6 in the Appendix. Finally, in order to clear up any further concerns, in Table A7 in the Appendix we use the monthly number of COVID-19 deaths as a dependent variable, and find similar results. This variable is less linked to the local labour structure of neighbourhoods because COVID-19 mortality depends much more on age and health, and it should not suffer from any type of estimation bias, as all deceased people were tested for COVID-19, and there is no heterogeneity in the way deaths are reported across neighbourhoods and types of jobs.

of COVID-19 cases in other neighbourhoods within the same LAD weighted by the pair-distance between neighbourhoods.

We control for unobserved time-variant heterogeneity at the local government level by including local authority fixed-effects θ_r, time fixed-effects λ_t, and local authority time trends γ_{rt}[8]. Residual time- and neighbourhood-varying observable factors are included in the term e_{it}. Thus, the coefficient of interest, α_1, is identified off the within-city neighbourhood variation in urban density prior to the pandemic.

4.2 Local Labour Market Composition Analysis

Next, we want to disentangle the role played by urban density from that played by local labour market composition in facilitating the spread of the virus. Specifically, we may expect 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 on-site. To do that, we modify Equation 4 by decomposing the residential (r) population in a neighbourhood i (N_i^r) into 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, with the variables being included in log terms:

$$\begin{aligned} COVID_{it} = \quad & \alpha_1 Popden_i + \alpha_2 HW_i^r + \alpha_3 KW_i^r + \alpha_4 NW_i^r + \\ & \beta_1 Empden_i + \beta_2 HW_i^w + \beta_3 KW_i^w + X_i'\Gamma + \lambda_t + \theta_r + \gamma_{r,t} + e_{it}, \end{aligned} \tag{5}$$

Because we control for the total resident (worker) population in X_i, the coefficients α_2-α_4 (β_2-β_3) reflect the percentage change in average COVID-19 cases from a one percent increase in the number of residents (workers) rather than residents (workers) in other non-essential on-site jobs (OW). We include the same control variables and fixed-effects as in our baseline specification.

4.3 Additional Analysis

We perform several additional analyses to better understand some of the mechanisms linking the composition of the local labour market with the spread of COVID-19. First, following (Desmet

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

and Wacziarg, 2021), we consider the dynamic evolution of the spread of the disease by allowing the model in Equation 4.2 to be fully flexible over time:

$$
\begin{aligned}
COVID_{it} = \quad & \alpha_{1,t} Popden_i + \alpha_{2,t} HW_i^r + \alpha_{3,t} KW_i^r + \alpha_{4,t} NW_i^r + \\
& \beta_{1,t} Empden_i + \beta_{2,t} HW_i^w + \beta_{3,t} KW_i^w + X_{i,t}' \Gamma + \gamma_{r,t} + e_{it},
\end{aligned}
\tag{6}
$$

where variables are as specified above. In practice, we estimate this as a series of cross-sectional regressions for each time period, through which we can 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 restricting on-site working only to jobs identified as keywork.

Secondly, we explore further the nature of keywork 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, deliveries, etc.).

Third, we explore the heterogeneity of our baseline results across different neighbourhood 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 local labour market composition and the spread of the virus is affected by the level of deprivation of the neighbourhood, most particularly when the spatial distribution of keyworkers is clustered around deprived areas. Furthermore, we combine this with dynamic analysis of the lockdown periods in order to understand whether the UK Government's public health measures may have had heterogeneous effects on limiting the contribution of the local labour market's composition to the spread of the virus depending on the socio-economic characteristics of neighbourhoods. This analysis will inform us about the social justice implications of the national lockdowns imposed in the UK, which may have disproportionately affected neighbourhoods with higher levels of deprivation because most of the resident population had jobs that could not be done from home. These workers would therefore have had to resume working on-site in order to avoid losing income. In an alternative specification reported in the Appendix, we investigate house crowding as 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 particularly relevant for neighbourhoods with high levels of resident keyworkers who continued to work on-site and were thus exposed to social contact throughout the pandemic, and it is something that remains relevant during 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, particularly in multi-generation households.

Finally, supplementing the robustness checks mentioned earlier, we perform several additional and sensitivity tests to validate our results. First, in Table A4 in the Appendix, we replicate the local neighbourhood 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 measure. Second, in Table A5 in the Appendix we exclude the weeks from January 2021 onward to ensure that our findings are not contaminated by the roll-out of COVID-19 vaccines provided for free to the UK's entire population started in late December 2020. Finally, in Table A8 in the Appendix we look at the relationship between population, employment density, neighbourhood labour structure, and COVID-19 weekly cases by distinguishing between MSOAs in small and large Travel To Work Area (TTWA) commuting areas. This analysis will further inform us about how local neighbourhood 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 4 in considering the overall measure of urban density. Column 2 differentiates between population and employment densities. Column 3 reports the results of regression model 4.2, in which we also consider the composition of resident and employed keyworkers and homeworkers at the MSOA neighbourhood level.[9]

[TABLE 1 HERE]

Urban density is significant in explaining higher levels of COVID-19 cases across neighbourhoods, although the magnitude of the effect is relatively small. On average, a 1 percent increase in urban density in Column 1 is associated with a 0.022 percent increase in cases. As shown in Column 2, we find that both population and employment densities are significant in explaining the

[9]Results using density measures based on satellite imagery data are consistent and available in Table A3 in the Appendix.

viral spread, which is 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 3, we present the results for estimating Equation 4.2. When conditioned on the types of workers in a neighbourhood, employment density and residential density are both 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 an increase in COVID-19 cases: 47 more resident keyworkers in a neighbourhood will lead to an increase of almost 2 COVID-19 cases per week. We interpret these results as showing that by working from home, residents in a neighbourhood were able to slow down the infection, preventing the spread of the virus from their place of work to the place where they live; the opposite holds in the case of keyworkers who kept working on-site 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 neighbourhood increases the incidence of COVID-19 cases across local residents, even though its statistical significance is weaker than that of other estimates. Specifically, we find an elasticity of -0.040 for WFH jobs, i.e. that 71 more jobs being done from home will decrease COVID-19 cases by 1 per week in the workplace neighbourhood. We find a positive effect of similar magnitude for keyworkers, where having 71 more keyworkers employed in a neighbourhood will 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 to explain the differences in the number

[10] However, population density seems to matter more than employment in neighbourhoods that are 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 A6 in the Appendix) and the monthly number of COVID-19 deaths (Table A7).

of COVID-19 cases between neighbourhoods. Following our empirical approach, we compare the cumulative number of COVID-19 cases over the period with the number of residents keyworkers and homeworkers for all combinations of MSOAs (which have, on average, similar population sizes) within each LAD in England. In this way we are able to calculate the share in the difference of COVID-19 cases that 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, the within-LAD differences in the number of keyworkers across MSOAs explain about 3.6% of the differences in the cumulative number of COVID-19 cases over the period of analysis; this is 2.05% in the case of keyworkers employed in the neighbourhood. On the contrary, larger positive differences in the number of residents as homeworkers explain almost 1.1% of the smaller number of COVID-19 cases between neighbourhoods (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, Eltham North, is in the 25th percentile of the national distribution of resident keyworkers (652) and has a cumulative number of 481 COVID-19 cases. The second, Abbey Wood North, is in the 75th percentile of the distribution with 955 resident keyworkers and 854 cases overall. Our estimates show that the larger number of resident keyworkers in Abbey Wood could explain 5.8% of the difference in between its COVID-19 cases and those of Eltham North. This exercise shows the significance of the local labour market composition to explain within-city differences in the spread of the virus, as a supplement to 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 in linking the labour composition of neighbourhoods with the spread of the COVID-19 virus by performing several analyses. First, in Figure 4, we examine the dynamic variation in the effect of residential and employee densities from the changes in the public health measures imposed by the UK Government. In the left panels, we report results for keyworkers, while results for homeworkers are reported on the right. To ease 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 open period (July-November

[12] For all MSOAs i and j combinations in each LAD r we calculate this as the difference in the number of keyworkers (homeworkers) and residents (workers) (L) multiplied by the relevant β^L coefficient estimated from Equation 4.2 and reported in Column 3 of Table 1, divided by the difference in the cumulative number of COVID-19 cases over the period March 2020-April 2021 (C): $\frac{\sum_{ijr} \frac{(L_{ir}-L_{jr})\times\beta^L}{(C_{ir}-C_{jr})}}{N_{ijr}}$.

2020). In particular, cases are significantly higher in neighbourhoods with more resident keyworkers during lockdown periods. This could be evidence that the presence of keyworkers residing in a neighbourhood, who had to remain working on-site throughout the pandemic and were thus more exposed to 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 open period. Partly reflecting evidence by Brandily et al. (2021), this may be related to the precautions taken by keyworkers as well as the health measures they had to follow throughout the pandemic to reduce the risks of infection inherent to their jobs. The effect may also be due to the greater social interaction over this period associated with certain jobs in the reference group, i.e. non-essential on-site workers 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 the hospitality sector helped the spread of the virus when it reopened in the period between the national lockdowns of 2020 (Fetzer, 2021). The effects are smaller and statistically weaker when we look at the role of keyworker employees, with an initial increase in cases in the first months of the first lockdown, and almost no effect in the following months.[13] We find opposite patterns for residents and employees who could work from home. Here, cases clearly reduced during lockdown periods in neighbourhoods where residents and workers were able to continue their economic activities from their dwellings without mixing with other households, and we observe almost no effect when social restrictions were lifted.

[FIGURE 4 HERE]

Overall, these results complement previous evidence (Di Porto et al., 2022) underlining the importance of analysing viral transmission by differentiating between where people live and where they work. Crucially, our findings provide some evidence of a trade-off in the shielding effect of lockdowns: the increased protection that WFH accords to the communities where such workers live and work has to be evaluated with respect to an increase in cases in the neighbourhoods with a higher share of resident keyworkers. This suggests that local employment structures have important social justice implications in relation to the public health measures introduced by many governments in their efforts to stop the spread of viral infections.

[13]Such differences may reflect the fact that keyworkers were likely to have been targeted for testing early on in the pandemic, when testing was scarce. With respect to this, it should be noted that we cannot rule out that the roll-out of COVID-19 testing may be correlated with the spatial within-city distribution of keyworkers. However, it is important to point out that by the time of the second lockdown, testing was fully rolled-out and widely available.

Heterogeneity Analysis

We further explore these aspects by looking at the heterogeneity of these results across the distribution of neighbourhood deprivation. In Figure 5, we interact our key variables of population and worker 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 neighbourhoods. We observe that the number of resident keyworkers in a neighbourhood significantly increases the incidence of COVID-19 cases, particularly in the most deprived MSOAs (fourth quartile - Q4). In contrast, having a larger number of residents working from home significantly reduces infections, more markedly so 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 required on-site presence throughout the pandemic, which increased 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 neighbourhood 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). Furthermore, we do not find clear evidence of heterogeneous effects in the case of the employment composition of workers in a MSOA; this drives the incidence of COVID-19 cases for both key and WFH workers only in relatively well-off neighbourhoods in the second quartile of the distribution.

[FIGURES 5 and 6 HERE]

We further investigate the role of neighbourhood deprivation in Figure 6 by analysing whether the public health measures introduced by the UK Government had heterogeneous effects on limiting the contribution of residents' and workers' employment structure in spreading the virus in a neighbourhood depending on its level of deprivation. This analysis could provide further information about the social justice implications of national lockdowns. Evidence from Figure 6 indicates that the previously discussed insights hold true particularly during lockdown periods, when keyworkers are the only ones allowed and required to work on-site. However, in contrast to Figure 5, we do not observe significant differences across quartiles of the 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 on-site occupations, including workers in retail and hospitality. We note that this result does not hold for resident keyworkers in the most deprived neighbourhoods, which might point to the fact that keyworkers resident in these neighbourhoods continued to spread the virus to their communities during non-lockdown periods to the same extent as non-essential workers who were more exposed to social interactions in the hospitality sectors. This could explain the overall stronger relationship between resident keyworkers and infection cases in the most deprived neighbourhoods, as estimated in Figure 5. The results differ when we consider employed keyworkers, pointing once again to the importance of considering where people live rather than simply where they work. Conversely, larger shares of WFH residents reduced the incidence of COVID-19 during lockdown periods, particularly in the least deprived areas. We do not find statistically significant differences outside of lockdowns for residents and employees who can work from home, suggesting that working from 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 existence of trade-offs in the introduction of lockdowns. Such policies may have shielded people who could work from home, and consequently their communities, in the most affluent areas, but they could also have increased the relative exposure and risk of contagion in the more deprived neighbourhoods 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 nature of the different keyworker jobs carried out in affluent and poor neighbourhoods 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, in that routine keywork occupations are mainly prevalent in disadvantaged areas. This is also shown in Table 2, where we observe the percentage of the top 5 most concentrated keyworker occupations in the top and bottom quartiles of neighbourhood deprivation. There is a much larger proportion of care workers and home carers in the bottom quartile as opposed to the top, whilst the opposite holds true 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 high-skill jobs (e.g. aircraft pilots, flight engineers, managers, directors, etc.) living in the most affluent areas, whereas 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 bottom quartile of neighbourhood deprivation as opposed to just over 10% in the top quartile.

[FIGURE 7 HERE]

[TABLES 2 and 3 HERE]

We explore the potential implications for the spread of viral infection of the differences in the distribution of high- and low-skill keywork jobs across neighbourhoods in Table 4. Here, for each keywork/homework occupation type for residents and workers, we distinguish between high-, medium- and low-skill occupations. It is evident that viral infection in neighbourhoods is mainly driven by medium- and low-skill keyworkers, both living and working in the area, such as food processing 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 neighbourhood. In line with this, we find an increase in cases in places with more low-skilled residents who could work from home. This could be driven by workers in these occupations having been pushed to work on-site in order to avoid losing income. The positive effect of residents working from home in the reduction of infection in their neighbourhoods is driven only by high-skilled professionals, who mostly live in the most affluent neighbourhoods as previously shown. These findings suggest that the uneven relationship between occupation type and viral infection across neighbourhoods 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, in which they are similar 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, having heterogeneous effects due to spatial variation in the skill intensity of keywork and WFH occupations of residents and workers across neighbourhoods.

[TABLE 4 HERE]

Finally, in Figure 8 we investigate how the role of jobs skill intensity varies across neighbourhood deprivation levels. Figures in panel (a) for residents show that the higher incidence of COVID-19 cases in a neighbourhood is mainly explained by the larger numbers of high-skilled keywork residents living in the most deprived areas. Analysing the data, we find that these occupations relate mostly to jobs such as medical practitioners, nurses, protective services, and care workers—professions that were all highly exposed to contagion risks during the pandemic. This effect might be significant only in the most deprived areas possibly because of the high level of crowding in multi-generational housing that is particularly common in deprived areas; this could have facilitated the spread of the virus from the residents' workplaces to the local community. However, we do not find any significant difference for low-skilled resident keyworkers across the deprivation distribution.

[FIGURE 8 HERE]

In addition, we notice that the negative relationship between resident homeworkers and COVID-19 cases is particularly strong in the case of high-skilled workers living in the most affluent neighbourhoods in the local authority, providing evidence corroborating the hypothesis previously discussed. However, when we focus on low-skilled resident homeworkers, we find a small but positive relationship with COVID-19 cases, particularly in affluent neighbourhoods in the local authority. These are predominately for jobs in sales, including elementary sales, stock control clerks, collector salespersons, and credit agents. It might be possible that given the nature of these occupations, these workers were asked by their companies to resume on-site work sooner than was the case for other high- and medium-skilled homeworkers, exposing them to contagion risk and helping the virus to spread in low-deprivation neighbourhoods.

When looking at the worker population in panel (b), we do not observe significant heterogeneity of worker skill intensity across neighbourhood 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 neighbourhood would significantly increase the spread of the virus. In contrast, having a larger number of low-skilled workers able to work from home would reduce the contagion in the workplace neighbourhood. 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 we consider the heterogeneity across neighbourhoods from the house crowding distribution.

6 Conclusions

In this paper, we contribute to the growing literature on the role the local economy structure played in the pandemic outbreak of COVID-19 by exploring the marked spatial variation in economic activities and local labour market composition. Exploring data at the neighbourhood (MSOA) level in England for the period between March 2020 and April 2021, we provide novel evidence on the complex role played by urban density in the COVID-19 pandemic 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 both traditional urban density measures and more novel approaches that use satellite imaging data, we show that residential density is particularly relevant, 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 of looking beyond population density to consider the role of the local labour market structure. Our findings indicate that not only does the residential density of an area play a general role in virus-spread, so does the employment structure of workers, suggesting the relevant importance of employment density in the spread of the virus. More importantly, we highlight that density of keyworkers is a significant driver of COVID-19 cases. This is a critical element, given that these workers provide an essential service that cannot be done remotely; such workers were therefore required to continue working on-site throughout the pandemic.

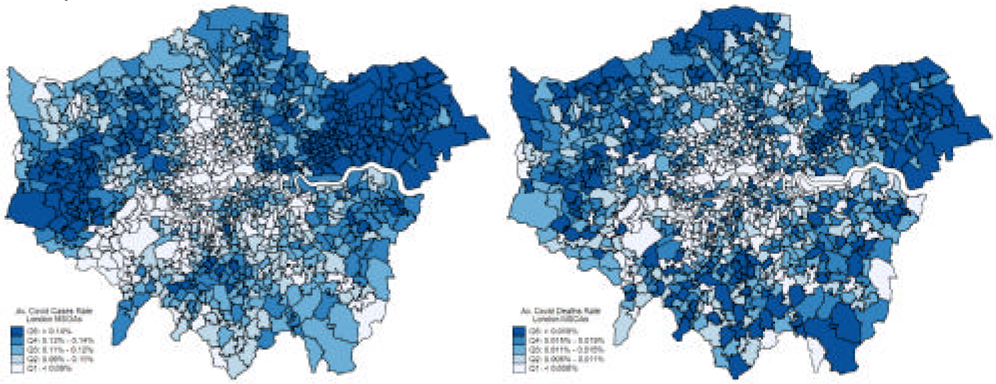
Third, while previous papers have highlighted the role of income distribution across places as a significant element in the COVID-19 pandemic (Desmet and Wacziarg, 2021; Rodríguez-Pose and Burlina, 2021), we provide novel findings pointing to a significant increase in risk across neighbourhoods in England that are characterised as having 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 and who 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. The increase in spread is mainly driven by medium- and low-skilled keyworkers, living largely in the most deprived areas of our cities, while the positive effect of working from home on 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). We show that the role played by lockdowns in breaking the link between density and COVID-19 is highly heterogeneous with respect to where people live and where they work. In particular, our results point to a significant trade-off in the shielding effect of lockdowns between keyworkers and workers who are able to work from home. This suggests that the effect of lockdowns may be somewhat limited at preventing intra-household contagion; this was particularly the case 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, which basically shifted the social and economic burden of viral infections from the affluent neighbourhoods, characterised by a large share of high-skilled residents able to work from home, to the most deprived areas within cities, which were mostly where the low-skilled keyworkers lived.

These results provide important insights for not only better understanding the determinants of diffusion of the virus, but equally for understanding which areas and group of workers remain more at risk of health consequences and economic loss as we transition towards endemic phase of viral infection. In particular, our findings may inform the design of policies by encouraging more consideration to be given to the nuanced role played by the employment structure of residents and workers (Basso et al., 2021), which accounts for the significant differences in the on-site working arrangements of key and non-essential workers. It also highlights 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 that prevent further negative economic shocks and inequalities in the welfare state (Stantcheva, 2022; Aspachs et al., 2022). They are also vital to implement more effective lockdown and other public health policies that can target more precisely the neighbourhoods that are more vulnerable from both an economic and contagion perspective. Our findings also provide insightful evidence that can predict how the virus might rapidly spread across the population based on the skill-intensity of workers and the level of deprivation of the neighbourhoods where they work and where they live. This information is key to managing the return of a large mass of homeworkers to the office during the endemic phase of COVID-19.

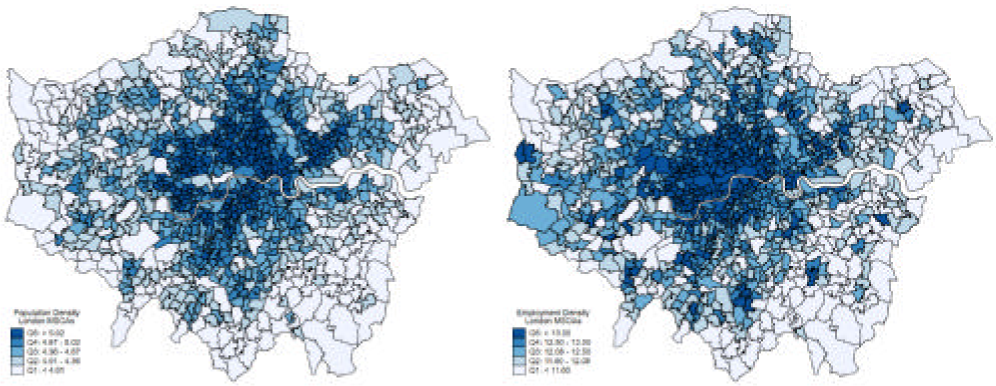
Tables and Figures

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.

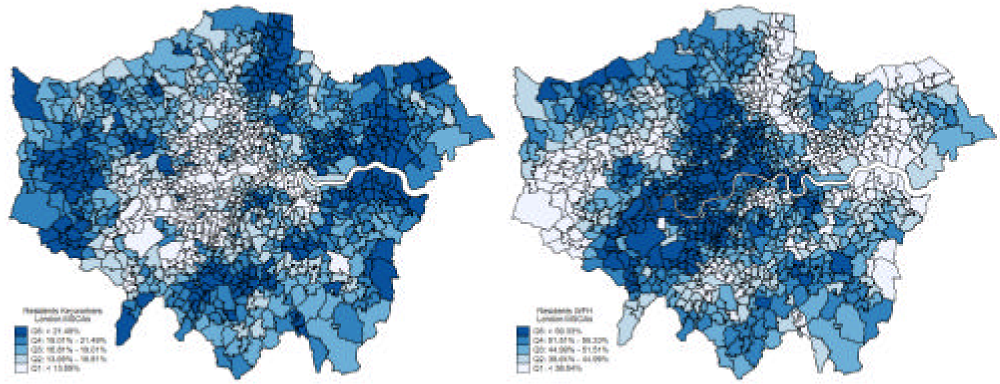
Figure 2: Population and Employment Density across MSOAs within the Greater London Authority.



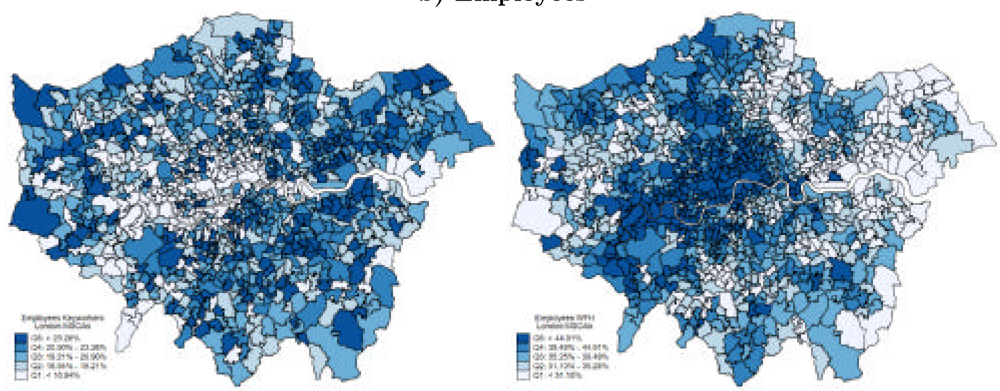
Notes: Elaboration based on ONS data for 2019. Density calculated over size of MSOA.

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



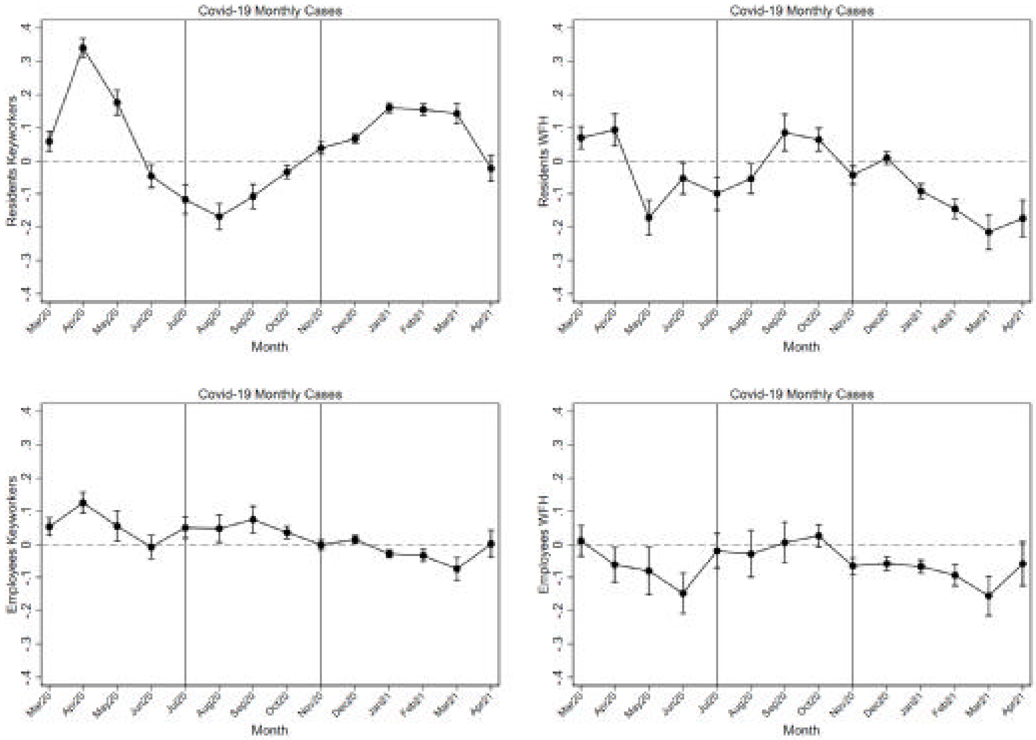
Notes: Elaboration based on ONS data for 2019. Shares calculated over total resident or working population in 2019.

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

	(1) Weekly Cases	(2) Weekly Cases	(3) Weekly Cases
Urban Density	0.0223***		
	(11.39)		
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	0.658***	0.663***	0.731***
	(67.29)	(64.34)	(8.62)
Employment	0.0079***	-0.0000589	0.0215
	(2.70)	(-0.01)	(1.11)
Share Elderly	0.1090***	0.116**	0.0793
	(2.50)	(2.66)	(1.69)
Share Children	0.504***	0.492***	0.266**
	(5.32)	(5.18)	(3.04)
Share White	-0.505***	-0.503***	-0.530***
	(-19.70)	(-19.53)	(-20.62)
House Crowding	0.037***	0.0388**	0.0296*
	(2.80)	(2.89)	(2.22)
Deprivation Index	0.192***	0.195***	0.0879*
	(10.14)	(10.23)	(2.41)
Pollution	0.045***	0.0461***	0.0463***
	(9.69)	(9.89)	(9.93)
No. Care Beds	0.016***	0.0167***	0.0163***
	(18.53)	(18.33)	(17.40)
Cases Spatial Lags	-0.0014***	-0.0014***	-0.00145***
	(-10.15)	(-10.08)	(-10.05)
LAD FE	Y	Y	Y
Time FE	Y	Y	Y
LAD*Time FE	Y	Y	Y
Observations	441285	441285	441285
R^2	0.811	0.820	0.821

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

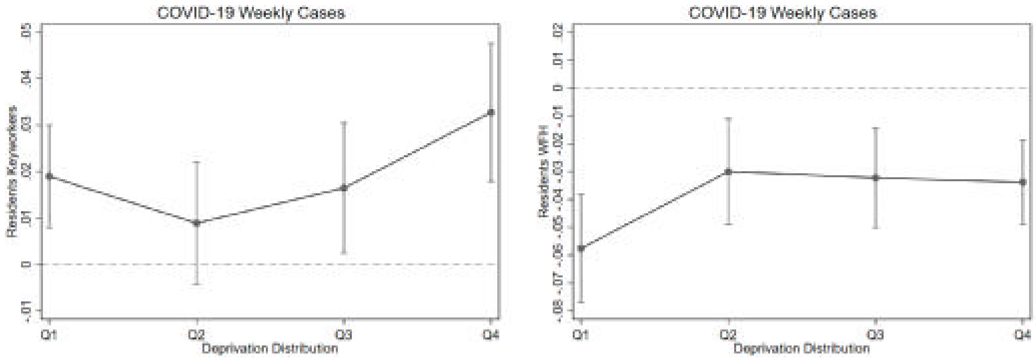
Figure 4: Dynamic relationship between neighbourhood labour structure and COVID-19 monthly cases.



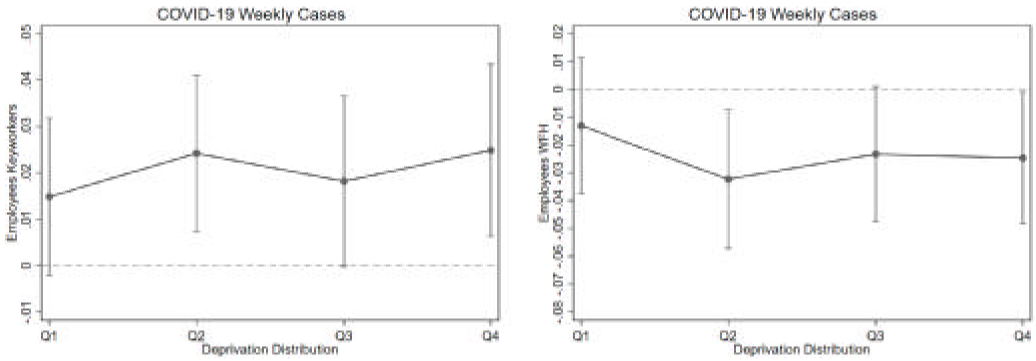
Notes: Markers represent beta coefficients from the log number of residents and employees in the MSOA who are defined as keyworkers or able to work from home. Different regression run for each month. Red lines show the end of the first national lockdown (04 July 2020) and the beginning of the second 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 care beds 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



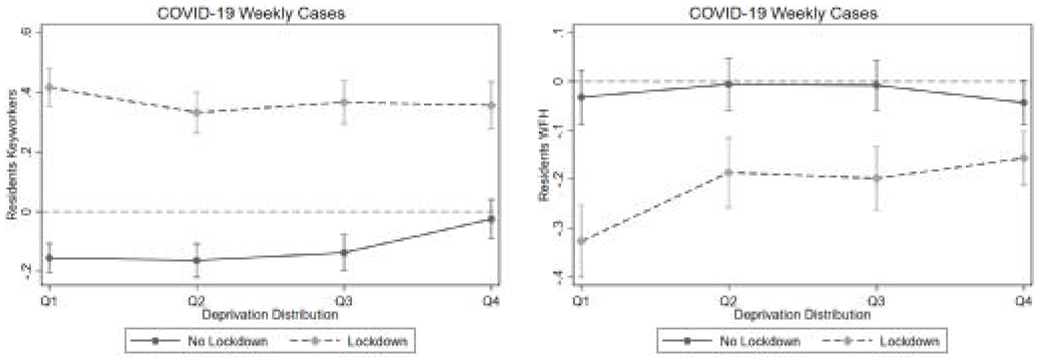
b) Employees



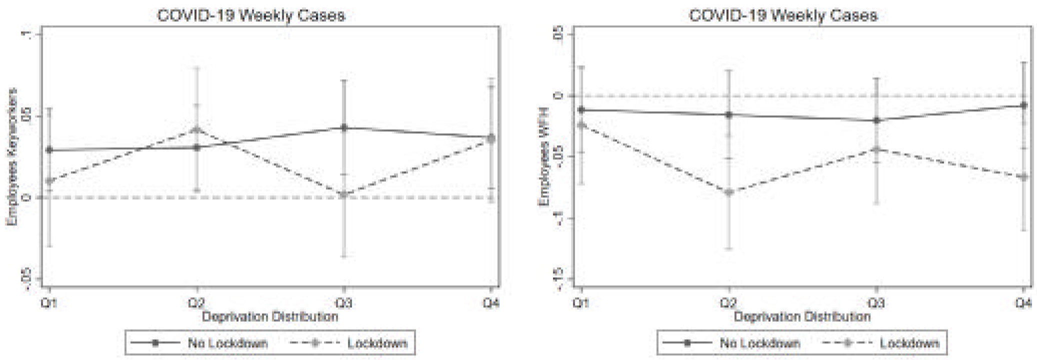
Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood deprivation distribution reported from least deprived (Q1) to most deprived (Q4) MSOAs. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment 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 care beds 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

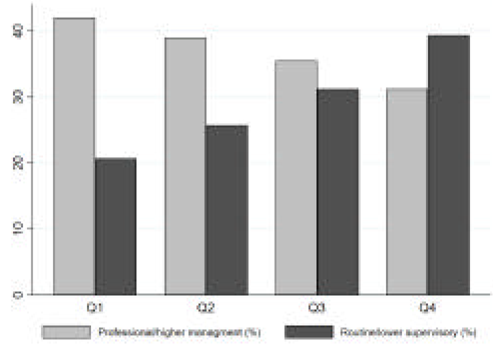


b) Employees



Notes: Beta coefficients reported. 95% confidence intervals included. Neighbourhood deprivation distribution reported from least deprived (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 care beds in the MSOA.

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



Notes: Neighbourhood deprivation distribution reported from least deprived (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 the keywork occupations that 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.

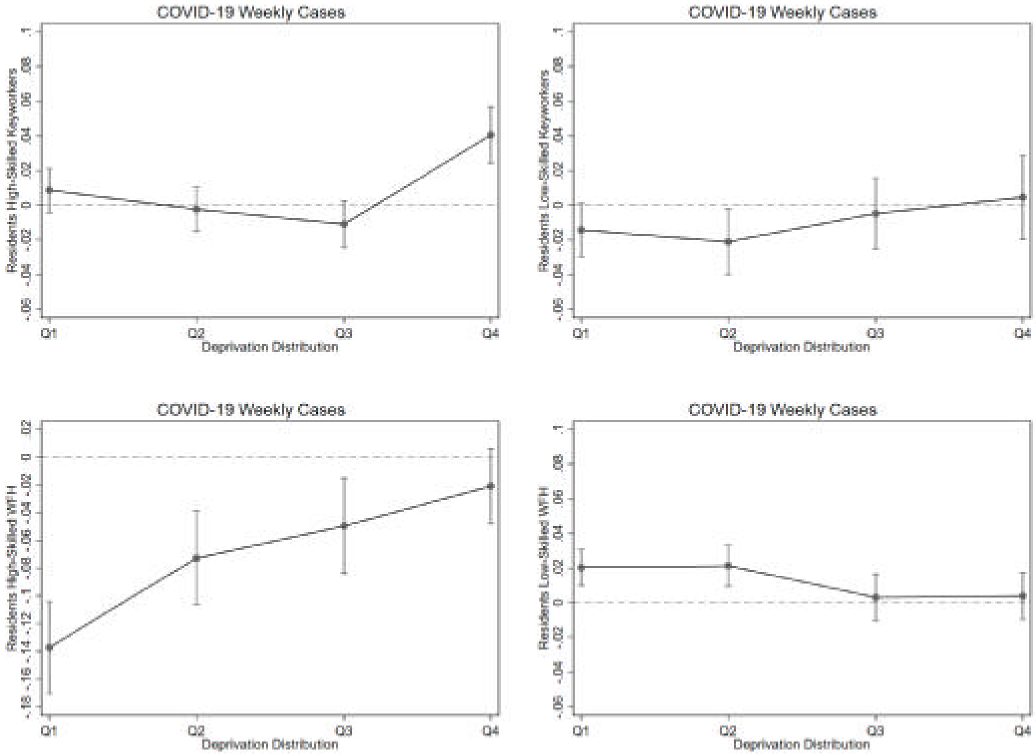
Table 4: Relationship between neighbourhood labour structure and COVID-19 weekly cases by MSOA by occupation skill intensity.

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					

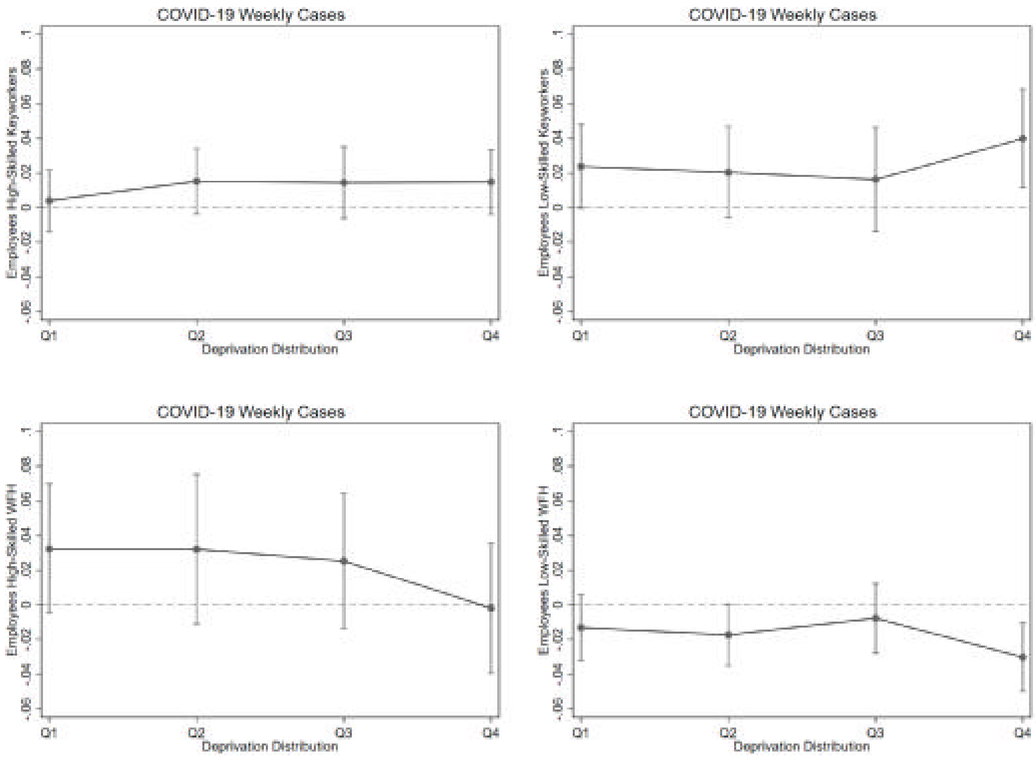
Notes: Robust standard errors clustered at the MSOA level. T-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: local authority fixed effects, time fixed-effect, local authority time trends, population density, employment density, dependent children (% of 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 care beds 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 deprived (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 care beds in the MSOA.

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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 as o_4, and in neighbourhood i by N^r_{i,o_4}. To identify the number of jobs that likely would have continued to be done on-site 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* (where *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 keywork occupations that require being on-site:

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

We also calculate the proportion of keywork jobs that are performed in each neighbourhood (workers may live in the same neighbourhood or elsewhere) as $keyworkers^w_i{}_i$. 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 on-site 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.

The proportion of homeworkers is calculated in a similar manner to keyworkers above. For jobs

[14] Four-digit occupation codes as defined by UK Standardized Occupational Classification.
[15] Keyworker 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 this link.
[16] Three-digit occupation codes as defined by UK Standardized Occupational Classification.

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 by workers in the neighbourhood 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 that 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

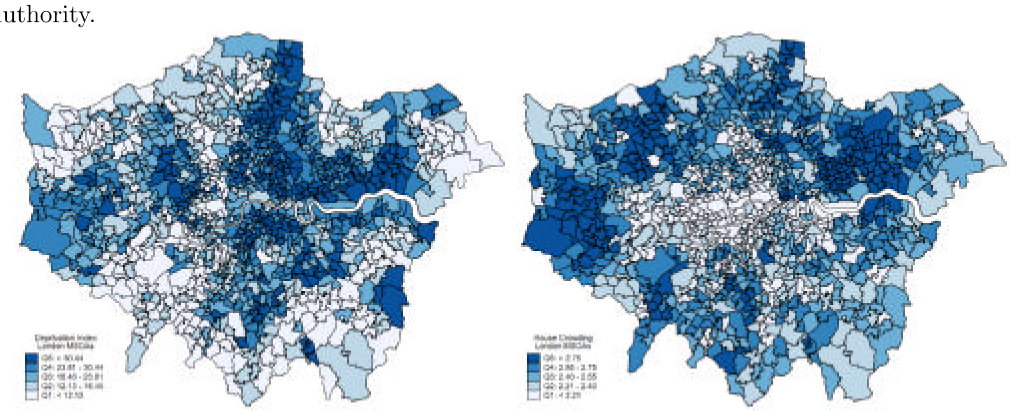
$$OW_i^w = N_i^w - HW_i^w - KW_i^W. \tag{A.6}$$

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 on-site jobs not categorised in the other two typologies.

Table A2: Summary statistics for main COVID-19 and neighbourhood 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.

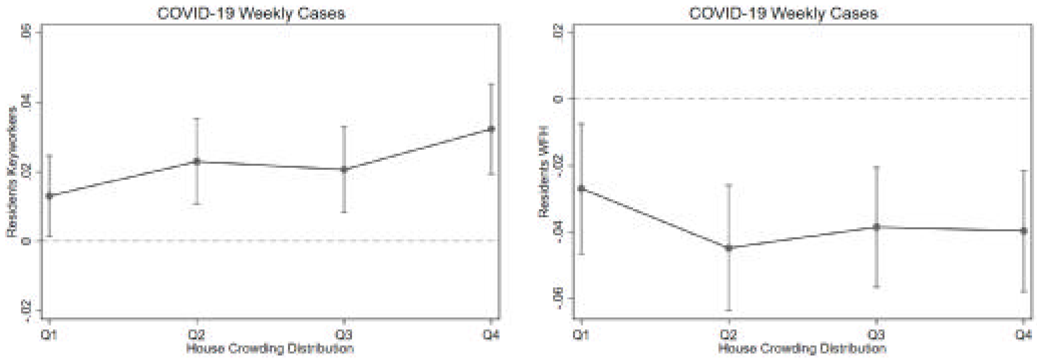
Table A3: Relationship between urban density and COVID-19 weekly cases by MSOA using satellite imagery data.

	(1) Weekly Cases	(2) Weekly Cases	(3) Weekly Cases
Satellite Density	0.010*		
	(2.44)		
Daytime Density		-0.004	-0.004
		(-1.83)	(-1.46)
Nighttime Density		0.007**	0.009***
		(3.09)	(3.91)
Residents Keyworkers			0.012**
			(3.27)
Residents WFH			-0.045***
			(-7.25)
Employees Keyworkers			0.028***
			(6.38)
Employees WFH			0.006
			(0.88)
Residents Not Employed			-0.038***
			(-4.04)
Population	0.098***	0.104***	0.148***
	(22.74)	(48.64)	(11.24)
Employees	0.002	0.004*	-0.028**
	(1.39)	(2.03)	(-2.97)
Share Elderly	-0.005*	-0.004	-0.006*
	(-2.14)	(-1.64)	(-2.38)
Share Children	0.013***	0.014***	0.008***
	(5.26)	(5.42)	(3.30)
Share White	-0.068***	-0.068***	-0.070***
	(-20.42)	(-20.23)	(-20.76)
House Crowding	0.003	0.004	0.000
	(1.28)	(1.47)	(0.02)
Deprivation Index	0.021***	0.021***	0.001
	(10.08)	(10.12)	(0.28)
Pollution	0.077***	0.078***	0.077***
	(14.52)	(14.70)	(14.63)
No. Care Beds	0.024***	0.024***	0.023***
	(19.30)	(19.28)	(18.08)
Cases Spatial Lags	-0.061***	-0.060***	-0.062***
	(-8.10)	(-8.04)	(-8.33)
LAD FE	Y	Y	Y
Time FE	Y	Y	Y
LAD*Time FE	Y	Y	Y
Observations	441285	441285	441285
R^2	0.820	0.820	0.820

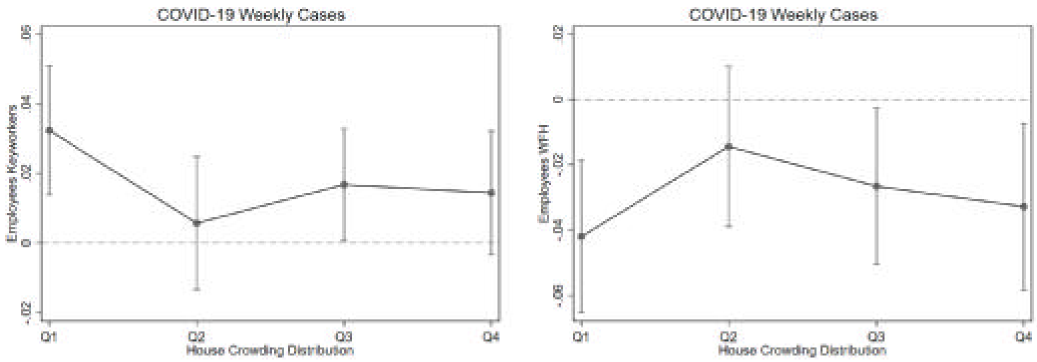
Notes: Robust standard errors clustered at the MSOA level. T-values reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 care beds in the MSOA.

Table A4: Relationship between population, employment density, neighbourhood labour structure and COVID-19 weekly cases by MSOA - Rates.

	(1) Weekly Cases	(2) Weekly Cases	(3) Weekly Cases
Urban Density	0.012***		
	(4.88)		
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
Time FE	Y	Y	Y
LAD*Time FE	Y	Y	Y
Observations	441285	441285	441285
R^2	0.825	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 care beds in the MSOA.

Table A5: Relationship between population, employment density, neighbourhood labour structure and COVID-19 weekly cases by MSOA - Pre-vaccination 2020 only.

	(1) Weekly Cases	(2) Weekly Cases	(3) Weekly Cases
Urban Density	0.022***		
	(10.87)		
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
Time FE	Y	Y	Y
LAD*Time FE	Y	Y	Y
Observations	298716	298716	298716
R^2	0.816	0.825	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 care beds in the MSOA.

Table A6: Relationship between population, employment density, neighbourhood labour structure and COVID-19 cumulative cases by MSOA.

	(1) Cum. Cases	(2) Cum. Cases	(3) Cum. Cases
Urban Density	0.032***		
	(10.11)		
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
Time FE	Y	Y	Y
LAD*Time FE	Y	Y	Y
Observations	6789	6789	6789
R^2	0.878	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 care beds in the MSOA.

Table A7: Relationship between population, employment density, neighbourhood labour structure and COVID-19 monthly deaths by MSOA.

	(1) Monthly Deaths	(2) Monthly Deaths	(3) Monthly Deaths
Urban Density	0.021***		
	(10.78)		
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
Time FE	Y	Y	Y
LAD*Time FE	Y	Y	Y
Observations	95046	95046	95046
R^2	0.586	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 care beds in the MSOA.

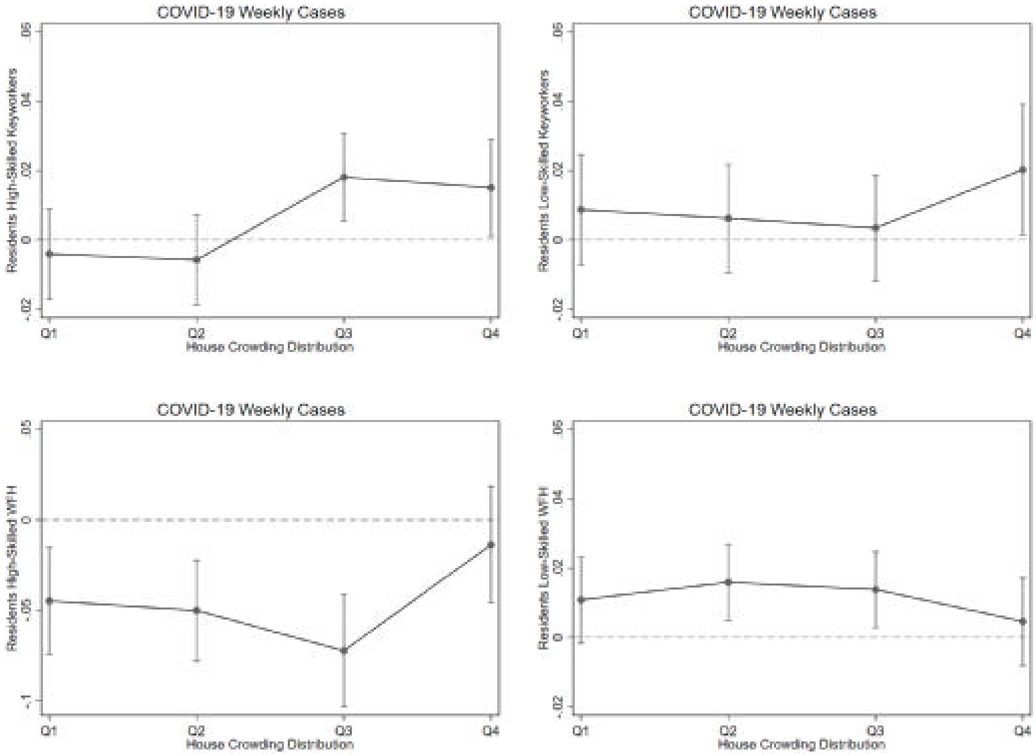
Table A8: Relationship between population, employment density, neighbourhood labour structure and COVID-19 weekly cases by MSOA in large and small TTWAs.

	(1)	(2)	(3)	(4)	(5)	(6)
		Small TTWAs			**Large TTWAs**	
	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases	Weekly Cases
Urban Density	0.024***			0.012***		
	(10.30)			(3.82)		
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
Time FE	Y	Y	Y	Y	Y	Y
LAD*Time FE	Y	Y	Y	Y	Y	Y
Observations	215995	215995	215995	223925	223925	223925
R^2	0.798	0.810	0.811	0.822	0.831	0.831

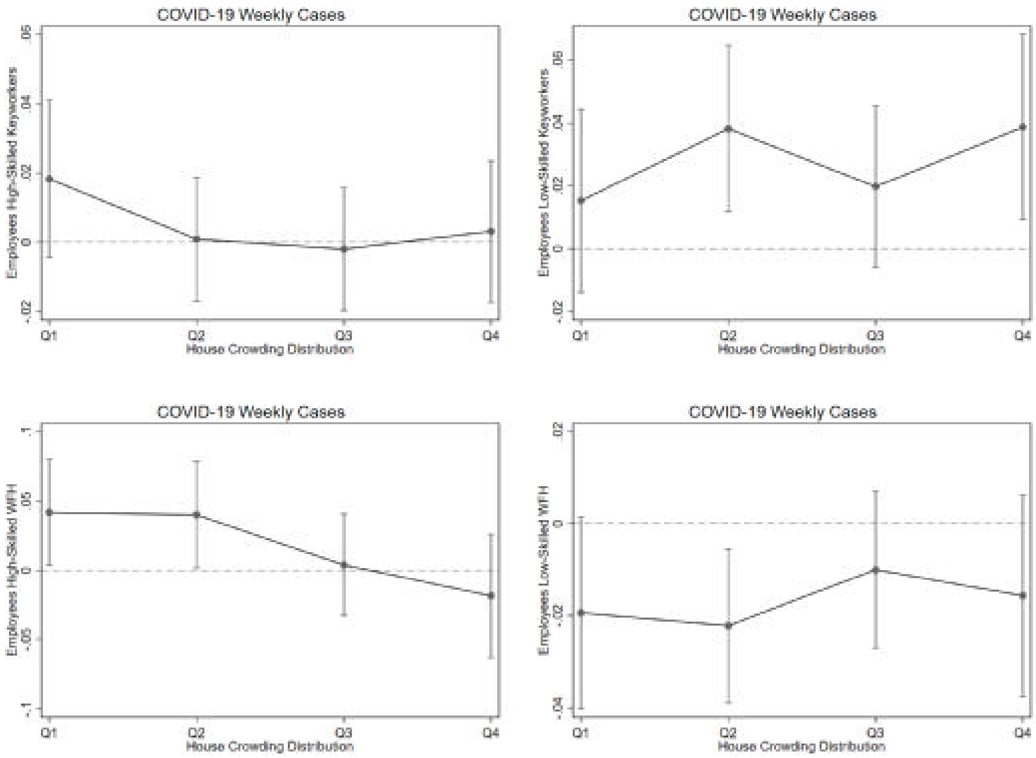
Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Control variables included: dependent children (% of pop), elderly (% of pop), white ethnicity (% of pop), log-population, log-employed residents,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

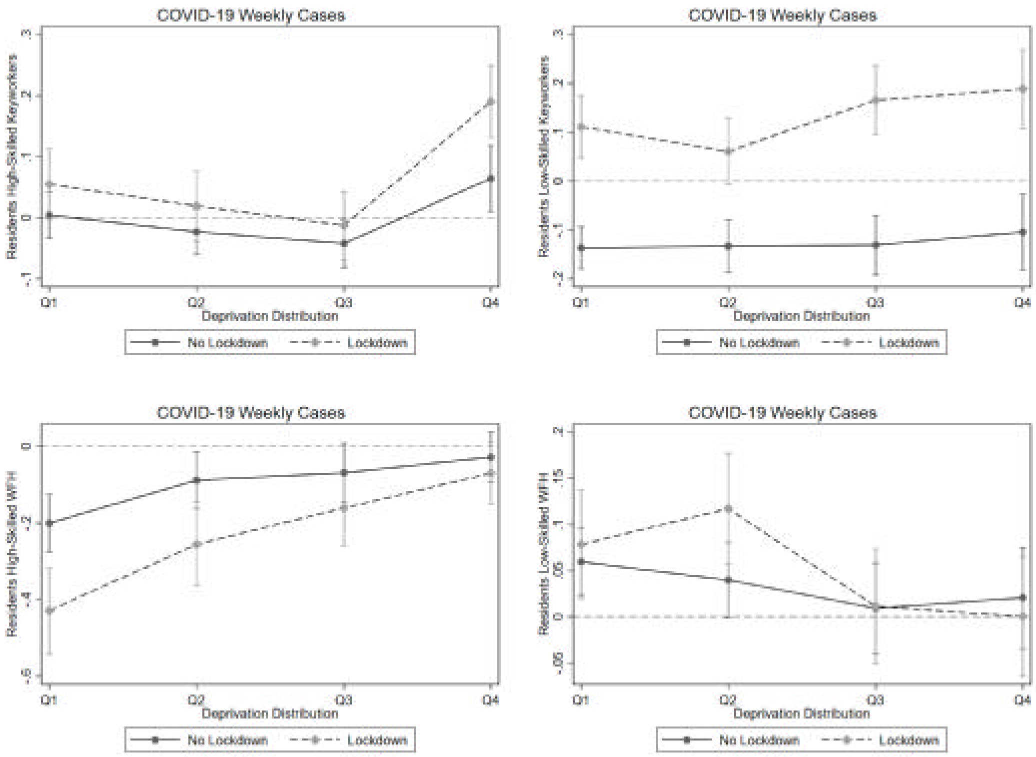
Table A9: Relationship between population, employment density, neighbourhood skilled labour structure and COVID-19 weekly cases by MSOA during lockdown periods.

	(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

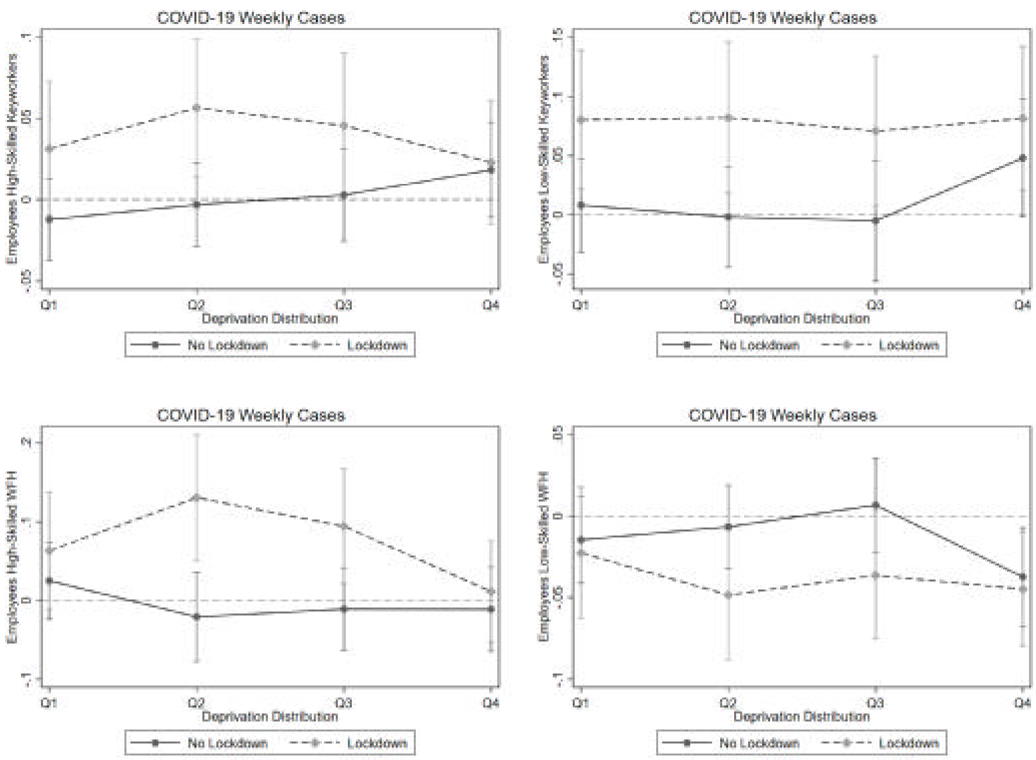
Notes: Robust standard errors clustered at the MSOA level. Beta coefficients reported and t-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Lockdown periods considered are March-May 2020, November 2020, and January-April 2021. Control variables included: population density, employment 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 care beds 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 deprived (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 care beds in the MSOA.