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ORIGINAL ARTICLE

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Neighbourhood labour structure, lockdown policies, and the uneven spread of COVID-19: within-city evidence from England

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Abstract

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 dataset across 6791 English neighbourhoods that distinguishes between people living (residents) and people working (workers) in a neighbourhood, and differentiate between jobs that can be done from home (homeworkers), jobs that likely continued on-site (keyworkers), and non-essential on-site jobs. We find that a 10 percentage points increase in keyworker jobs among residents is associated with 3.15 more cases per 1000 (4.8% relative to the mean), while a 10 percentage points increase in homeworker jobs among residents is associated with a decrease of 7.74 cases per 1000 (11.8% relative to the mean). Results for the composition of workers show the same sign, but smaller magnitudes. A dynamic analysis of the monthly incidence of reported cases shows that these relationships are particularly strong during lockdown periods. These results are heterogeneous across neighbourhoods, with larger positive effect of keyworkers, and lower protective effect of homeworkers, in higher deprivation areas. We explore the role of occupation skill intensity in driving these neighbourhood differences. These findings highlight important asymmetries in the distributional impact of the policy response to COVID-19.

1 | INTRODUCTION

The spatial heterogeneity of the COVID-19 outbreak has been a striking feature from the outset. Several studies have shown how this variation reflects differences in socioeconomic characteristics across locations, including income and age distribution, and the quality of healthcare and institutions (Carozzi *et al.* 2024; Desmet and Wacziarg 2022; Rodríguez-Pose and Burlina 2021; McCann *et al.* 2022). 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 2024; Stadnytskyi *et al.* 2020; WHO 2021). 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 2022; Almagro and Orane-Hutchinson 2022; Carozzi *et al.* 2024; Ascani *et al.* 2021a; Armillei *et al.* 2021; McCann *et al.* 2022), 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 examine explicitly 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 dynamic heterogeneous effects for each of these groups across levels of neighbourhood deprivation, lockdown policies periods, and occupation skill intensity.

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 6791 neighbourhoods across England.[1] These data have the important feature of offering neighbourhood-level information on the labour structure of workers and residents by occupation,[2] allowing us to exploit within-city variation in 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] the only ones allowed to continue working on-site during lockdown periods. 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 importance of density in a neighbourhood—both density of residents and density of workers—for viral spread is statistically significant but small in magnitude. A 1% increase in the residential population per hectare of land is associated with a 0.013 increase in COVID-19 cases per 1000, and a 1% increase in worker population per hectare of land is associated with a 0.016 decrease in COVID-19 cases per 1000.

Second, neighbourhood labour structure is particularly important in explaining within-city variation, over and above population density and other confounders. We find that a 10 percentage points increase in keyworker jobs among residents is associated with 3.15 more cases per 1000 (4.8% relative to the mean), while a 10 percentage points increase in homeworker jobs among residents is associated with a decrease of 7.74 cases per 1000 (11.8% relative to the mean). We find similar results, although much smaller in magnitude, for the composition of workers in a neighbourhood. A 10 percentage points increase in the keyworkers among neighbourhood employment is associated with an increase in the COVID-19 rate of 1.46 cases per 1000 people (2.2% relative to the mean), while a 10 percentage points increase in the rate of jobs able to be done remotely reduces the COVID-19 rate in the local population by 0.17 cases per 1000 people (0.2% relative to the mean).

Third, the relationship between neighbourhood labour structure and the spread of COVID-19 is particularly important during lockdown periods. A dynamic analysis of monthly cases shows that the positive effect of keyworkers, and negative effect of homeworkers, was particularly strong during the second lockdown period, beginning in November 2020.

Fourth, the importance of the occupational composition of residents for the spread of COVID-19 varies based on the neighbourhood's deprivation level. Compared to low-deprivation neighbourhoods, in high-deprivation neighbourhoods we see a stronger positive association between reported COVID-19 cases and the share of residents who are keyworkers, and a weaker negative association between reported COVID-19 cases and the share of residents who are homeworkers. We investigate the mechanisms driving this with a detailed examination of differences in skill intensity of occupations across the neighbourhood deprivation distribution. These patterns are less clear when we look at how the effect of a neighbourhood's working population on COVID-19 cases varies according to deprivation.

We perform a number of robustness checks on our results. Our main results are robust to different measures of density, different measures of COVID-19 spread, and alternative specifications of the estimating equation, including the inclusion/exclusion of local authority fixed effects.

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 densities in spreading the virus (Almagro and Orane-Hutchinson 2022; Ascani *et al.* 2021a; Di Porto *et al.* 2022), and recent studies on the role of labour mobility on the spread of COVID-19 (Ascani *et al.* 2021b; Borsati *et al.* 2023), 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, which has so far received limited attention. This also distinguishes this paper from recent work by Almagro *et al.* (2023), using cell-phone mobility data to study the effect of greater out-of-home mobility and within-home crowding on the risk of COVID-19 hospitalization.

Second, we extend previous studies conducted at broad levels of spatial aggregation, where data are considered at provincial or regional level, by offering country-wide evidence about within-city variation in COVID-19 morbidity. Focusing on neighbourhood areas, where interpersonal contact is more likely to occur (Perles *et al.* 2021), our analysis provides complementary insights to prior literature by taking into account the highly localized dynamics in the diffusion of COVID-19 within the urban environment (Kuebart and Stabler 2020; Chang *et al.* 2021) and the potential effect of omitted neighbourhood characteristics (Glaeser *et al.* 2022), including differences in amenities, public spaces and residential preferences, in driving the significant variation in contagion at the micro level. 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 socioeconomic 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.* 2022; 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 neighbourhood deprivation.

Disentangling the black box of density to identify more precisely the relationship between proximity and viral transmission is critical to inform policy approaches in the endemic phase of the disease (Lewis 2021; Phillips 2021) and for future pandemic events (Marani *et al.* 2021; Duranton and Handbury 2023). Our findings provide 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, thereby supporting the design of policies addressing 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, our analysis has important implications for public health policy, bringing to the fore the need to evaluate possible asymmetries in the distributional effects of lockdowns and similar measures targeting mobility, especially for the most deprived neighbourhoods in the country. Evidencing higher risk exposure for keyworkers in deprived areas vis-à-vis workers who are able to work from home in more affluent neighbourhoods, our results can inform and provide support for the implementation of public transfers and targeted policies for the most affected workers and households (Basso *et al.* 2022; Aspachs *et al.* 2022).

The structure of the paper is as follows. In Section II, 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 III describes the data used. Section IV discusses the research design for the empirical analysis. Results are presented in Section V. Section VI 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 emerged rapidly 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 2022; Sá 2020; Desmet and Wacziarg 2022). 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 1918–19 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 urbanized 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.* (2021a) 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.* (2024) 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 urbanized areas. Conversely, Wong and Li (2020) show that population density is an effective predictor of cumulative infection cases in the USA 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 (2022) draw on county-level data on COVID-19 reported cases and deaths in the USA 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 kilometre 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-code level (Almagro and Orane-Hutchinson 2022; Guha *et al.* 2020). Similar results have been found from analysing Middle Super Output Areas (MSOAs) in England and Wales (Sá 2020). Conversely, focusing on Italian municipalities, Armillei *et al.* (2021) 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 close contact—as underlined by the consistent effect of house crowding proxies—that matters. Thus COVID-19 cases result from highly localized interactions; these are not simply a function of being in a large urban area as opposed to a smaller city environment, but rather are 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 localized nature are inherently connected to the structure of the local economy. Ascani *et al.* (2021a) explore a spatial autoregressive model of COVID-19 cases in the provinces (NUTS3) 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 *et al.* (2021) highlight similar elements, with the share of industrial and trade employment being positively associated with excess mortality, while the service employment share is found to have a negative relationship. Almagro and Orane-Hutchinson (2022) 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 *et al.* 2021; Desmet and Wacziarg 2022)—is no longer significant once occupation variables are controlled for (Almagro and Orane-Hutchinson 2022). Finally, recent contributions have explored the impact of essential workers and essential occupations, evidencing a positive effect on the spread of COVID-19 (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 characterized by strong and dynamic policy intervention aimed at restricting mobility, including stay-at-home orders in the USA, 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 6 January at the onset of the third wave. This final lockdown measure started to relax from March 2021.

As shown by Glaeser *et al.* (2022), who explored zip-code-level data for selected cities in the USA, 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). Complementary evidence is offered by the recent strand of research looking specifically at the relationship between labour mobility and the spread of COVID-19, pointing to a significant role of individuals' mobility as well as the position of municipalities within a network of commuting flows on disease transmission and depth of the shock (Ascani *et al.* 2021b; Borsati *et al.* 2023). 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.* (2021) 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 heterogeneous effects across different channels of COVID-19 transmission. Looking at mobility in labour market areas across Italy, Ascani *et al.* (2021b) suggest that blocking non-essential activities only partly reduces disease transmission, noting the effects of individuals' mobility as being particularly marked in areas with a larger presence of essential sectors. 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 2022). 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 mitigate transmission only in occupations that have to remain in operation during these mobility restrictions. Interestingly, the results by Almagro and Orane-Hutchinson (2022) 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 localized. In particular, we would expect density to drive transmission mostly in specific settings, where contact is more persistent and sustained. This suggests that 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, the level of deprivation experienced may result in a higher incidence of COVID-19, as more difficult neighbourhood conditions lead to higher levels of inter- and 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 work-from-home 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 characterized by higher levels of COVID-19 incidence. Furthermore, in such a case, very similar dynamics should be expected with regard to the role played by neighbourhood deprivation. This 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 urban density and COVID-19 can be expected to be more marked, as they reduce transmission by limiting social interactions. However, this may not be the case in areas with higher population density. Reflecting previous findings (Almagro and Orane-Hutchinson 2022), 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 deprivation levels, where social interactions and mixing of households are more likely to remain elevated. In addition, lockdown policies are also more likely to shift contagion towards the only category of workers still required to work on site and in person, keyworkers, and as a consequence the communities where they live and work.

3 | DATA

Our analysis is based on several datasets linked together at the neighbourhood level. We define a neighbourhood as an MSOA, using the geographic hierarchy nomenclature of the UK Office for National Statistics (ONS). We consider all 6791 MSOAs in England, which have mean area 19 km^2 and average population 7000 people (around 3000 households). Towns and cities are defined as Local Authority Districts (LADs), 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 administered either at the national level or at LAD level. For simplicity, we will refer to MSOAs as neighbourhoods and LADs as cities for the remainder of the paper.

Data reflect the period between March 2020 and April 2021. This period of time includes: (i) the first nationwide lockdown (26 March 2020 to 4 July 2020); (ii) the temporary lifting of many public health restrictions, including the reopening of non-essential businesses (4 July 2020 to 5 November 2020); (iii) the second nationwide lockdown (5 November 2020 to 12 April 2021); (iv) the lifting of lockdown restrictions and reopening of non-essential businesses (12 April 2021).

3.1 | COVID-19 data

Data on the spread of the COVID-19 pandemic in the UK at the neighbourhood level are provided by the ONS. The number of COVID-19 reported cases in each neighbourhood is registered weekly, while COVID-19 related deaths are reported monthly for each neighbourhood.

Figure 1 maps COVID-19 cases and deaths for neighbourhoods across the areas that make up Greater London and the city of Sheffield, as examples. There are stark differences in the numbers of COVID-19 cases and deaths across neighbourhoods, even between those that are adjacent or fall within the same city. For instance, we can see that while COVID-19 reported cases seem to be mostly clustered in certain areas, the east and west of the Greater London Authority and the east of Sheffield—the most deprived areas in these two cities—COVID-related deaths are much more randomly distributed, even extending to the more affluent neighbourhoods.

3.2 | Urban, resident and worker densities

Total residential population counts, and employment counts by occupation, for each neighbourhood are provided by the ONS. While residential population counts reflect 2018 values, employment counts are based on the 2011 population census. To provide estimates of 2018 employment counts at the neighbourhood level, we follow a Bartik shift–share approach (Goldsmith-Pinkham *et al.* 2020), scaling the 2011 census counts, for each occupation and neighbourhood, by the percentage change in employment for each occupation nationally between 2011 and 2018.

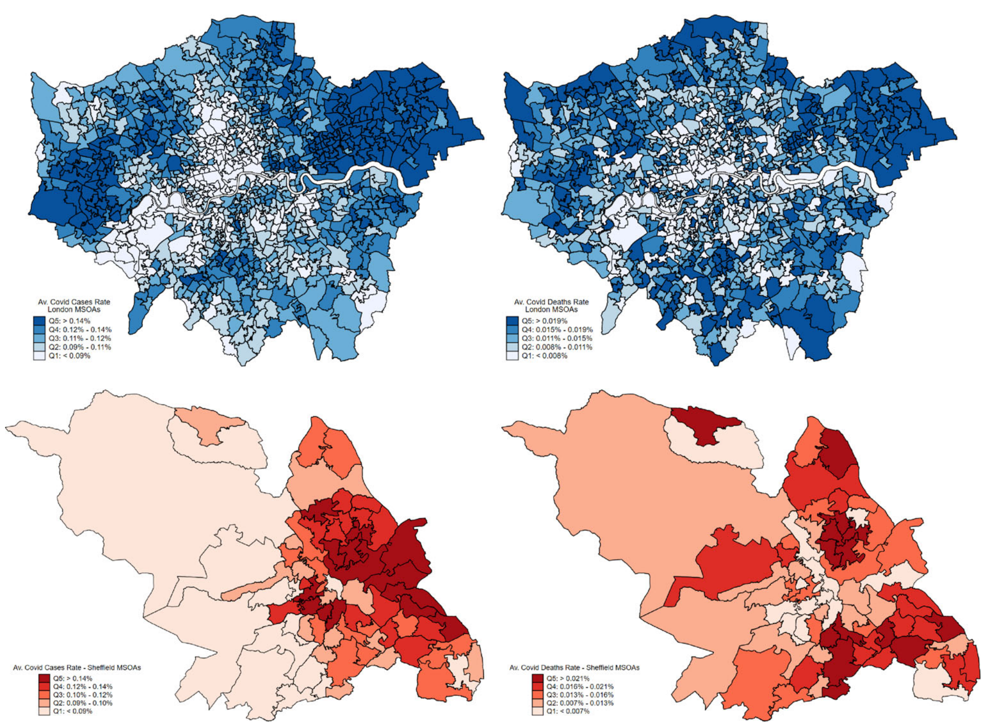


FIGURE 1 Average COVID-19 cases and deaths rates across MSOAs within the Greater London Authority and Sheffield Local Authority. *Notes*: Figures are based on ONS data for the period March 2020 to April 2021. Rates calculated over total population in 2018.

We calculate resident and worker densities in a conventional way, dividing population or employment counts by the total hectares of land size for each MSOA:

$$Res.Den_i = \frac{N_i^r}{Area_i}, \quad Wrk.Den_i = \frac{N_i^w}{Area_i}, \tag{1}$$

where N_i^r is the number of residents in MSOA i, N_i^w is the number of workers who work in MSOA i, and $Area_i$ is the total number of hectares of land covered by i.

From these data, we also derive an overall measure of urban density that takes into account the sum of residents and employees in a given neighbourhood divided by the MSOA land area. Roughly speaking, this provides us with an estimate for both the daytime, or working hours, and nighttime population of a neighbourhood. In our main specification we calculate this as

$$Urb.Den_i = \frac{NW_i^r + \left(0.67 \times N_i^r\right) + \left(0.33 \times N_i^w\right)}{Area_i}. \tag{2}$$

In order to limit measurement error and double counting when considering both employees and residents together in a density measure (as discussed in Duranton and Turner 2018), the numerator of equation (2) includes the number of non-working residents (NW_i^r) plus the number of working residents weighted by the time in a day that we assume they spend not working in their neighbourhood (67% of their time on average, about 16 hours), and the number of workers weighted by the time in a day that they spend working in the neighbourhood (approximately 33% of their time, around 8 hours a day). Notice that working residents who work in the neighbourhood where they live will be accounted for 67% of the time in N_i^r and for 33% in N_i^w.

Figure 2 provides a visual description of the different distributions of residents and workers, and overall urban density, across neighbourhoods in London and Sheffield, showing a strong concentration for all three measures in the city centres. This evidence sheds light on how traditional population density measures used previously might not be capturing effectively the distributions of where people live and where they work. Even more importantly, the comparison with Figure 1 shows an opposite spatial distribution of COVID-19 cases and deaths, which are clustered mainly in suburban and peripheral areas, with respect to the population and employment densities, which are concentrated mostly in city centres. This indicates the need to use 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.

3.3 | Residents and workers local labour market composition

We further decompose the employment compositions of residents (r) and workers (w) in each neighbourhood (i) according to the number of keyworkers, homeworkers and other types of jobs. The 2011 UK Population Census provides information on the number of residents (N_i^r) and the number of workers (N_i^w), by occupation, in each neighbourhood. We use this information to decompose the neighbourhood residential and working populations into the following groups:[4]

$$N_i^r = KW_i^r + HW_i^r + OW_i^r + NW_i^r, \tag{3}$$

$$N_i^w = KW_i^w + HW_i^w + OW_i^w. \tag{4}$$

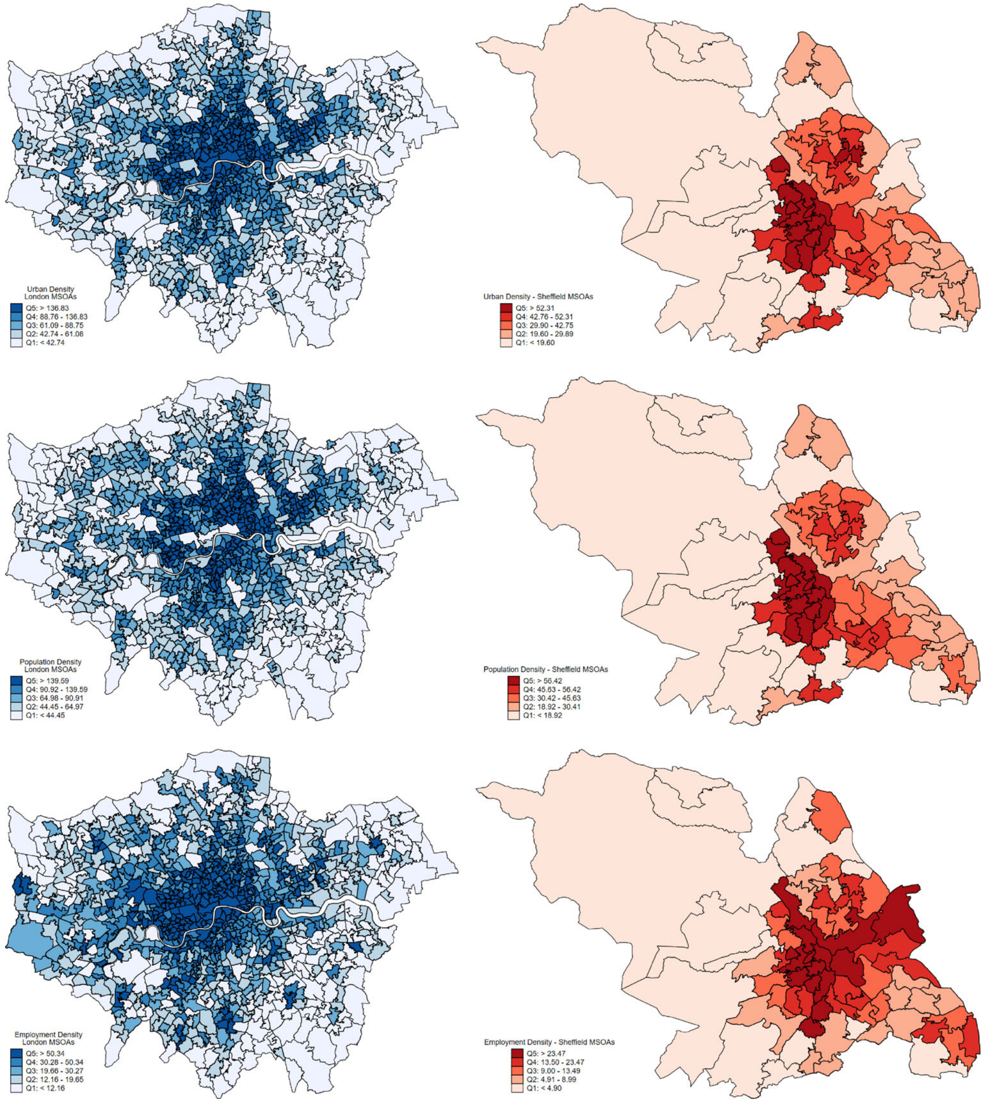


FIGURE 2 Urban, resident and worker densities across MSOAs within the Greater London Authority and Sheffield Local Authority. *Notes*: Figures are based on ONS data for 2018. Density calculated over size of MSOA.

Variables KW_i^r and KW_i^w measure the number of people in an occupation denoted as keywork, who likely continued working on site throughout the pandemic lockdowns, such as hospital staff, primary educators, critical retail staff and public transport workers. In contrast, HW_i^r and HW_i^w are the numbers of homeworkers, people who would have been able to do a significant portion of their job from home. Finally, all other workers, OW_i^r and OW_i^w, reflect 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 non-essential retail and hospitality. 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 workers reference tables' (ONS 2020). These identify the occupations that were legally allowed to be carried out outside the home during the national lockdowns. Finally, NW_i^r is the number of residents in the neighbourhood who do not work, including children and retirees. Of course, we observe this group only for the residential population, not the working population. We provide a detailed explanation of these calculations in Appendix A. In Appendix Table A1, we provide details of the occupations assigned to each group, as well as a table of representative jobs for each group.

Figures 3 and 4 supplement Figure 2 by showing a much more nuanced distribution of where keyworkers and homeworkers live, and where they work across neighbourhoods in London and Sheffield. 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 both metropolitan areas, which are also characterized 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 homeworkers, reported in the right-hand images of Figures 3(a) and 4(a). Similarly, we observe a more sparse distribution of where keyworkers work, in that we cannot identify specific spatial clusters, while the workplaces of homeworkers are mostly concentrated in the central business districts and in the south-west of the city, reflecting the distribution of white-collar jobs.

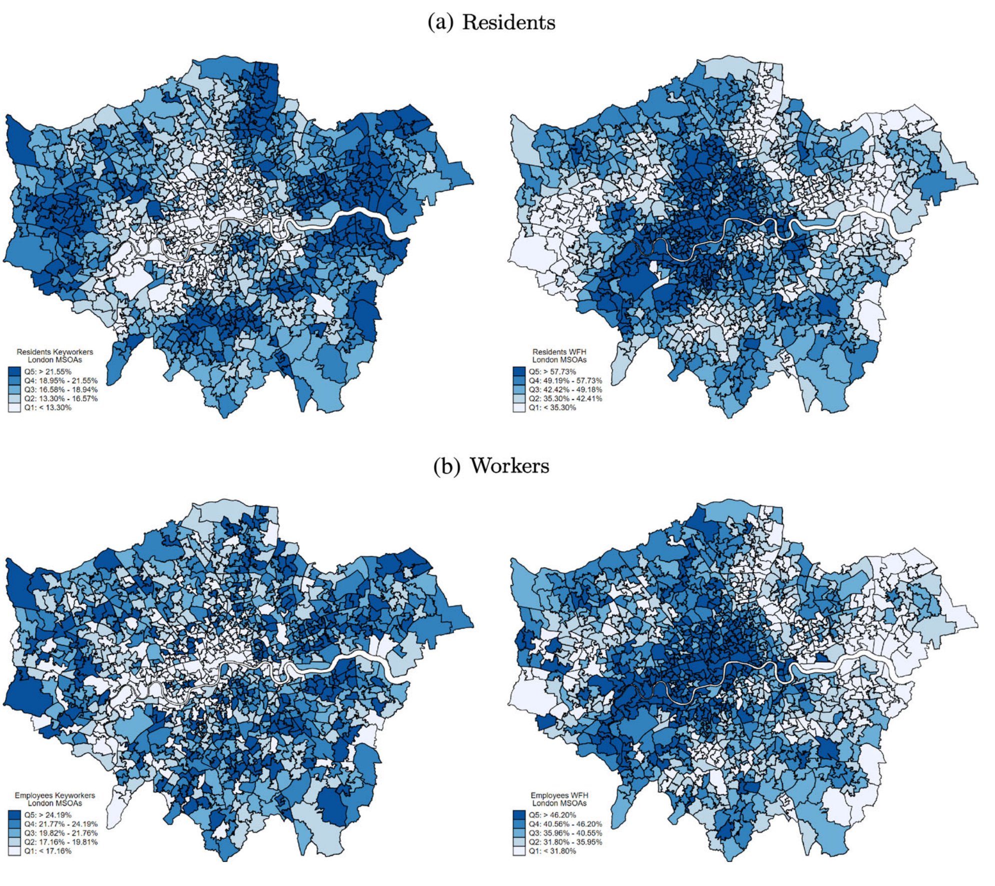


FIGURE 3 Shares of residents and workers (keyworkers and homeworkers) across MSOAs within the Greater London Authority. *Notes*: Figures are based on ONS data for 2011 and 2018. Shares calculated over total resident and worker populations in the MSOA in 2018.

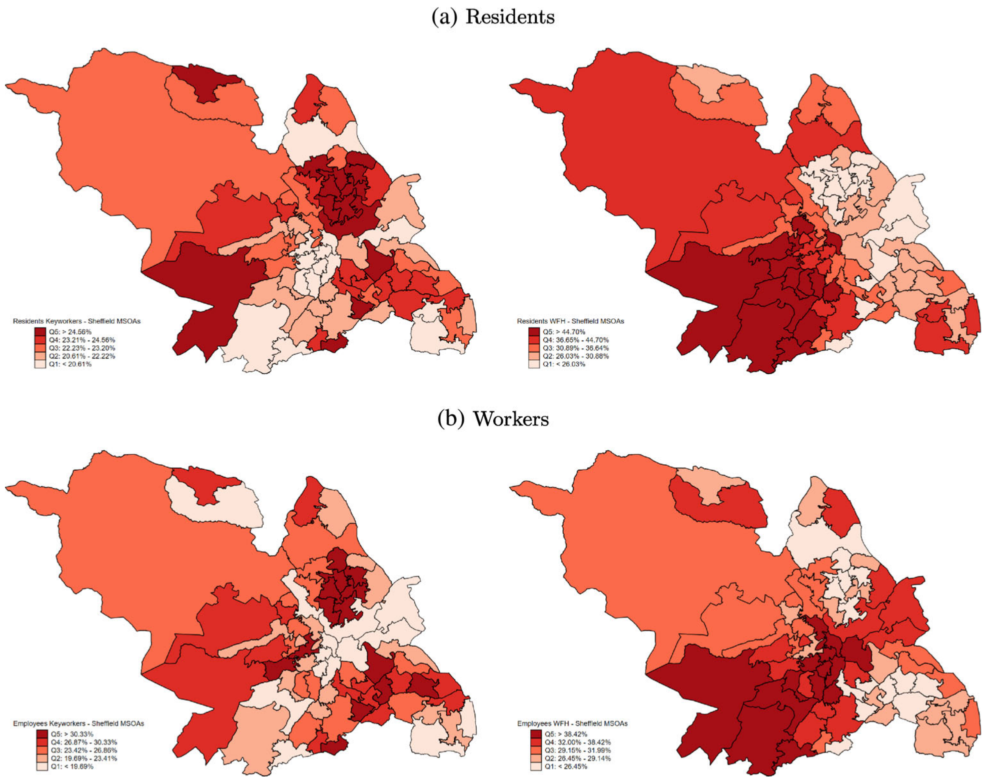


FIGURE 4 Shares of residents and workers (keyworkers and homeworkers) across MSOAs within Sheffield Local Authority. *Notes*: Figures are based on ONS data for 2011 and 2018. Shares calculated over total resident and worker populations in the MSOA in 2018.

3.4 | Other data

We gather additional data about the characteristics of neighbourhoods that might explain the spatial spread of the virus within cities according to previous studies. First, we obtain further information on each neighbourhood's resident population from the ONS Nomis 2018 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 socioeconomic 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 English indices of deprivation.[5] The level of particulate matter (PM2.5), 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]

4 | METHODOLOGY

We first look at the role of urban density in facilitating the spread of the COVID-19 virus, as analysed similarly in previous studies (Wong and Li 2020; Allcott *et al.* 2020; Desmet and

Wacziarg 2022; Almagro and Orane-Hutchinson 2022; Carozzi *et al.* 2024), by estimating the baseline model

$$COVID_i = \alpha_1\ Density_i + X_i'\ \Gamma + \theta_r + e_i. \tag{5}$$

The dependent variable $COVID_i$ reflects the cumulative number of COVID-19 reported cases scaled by 1000 residents in each neighbourhood i. We focus mainly 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 minimize the negative effect on the economy.

The primary independent variable of interest, $Density_i$, represents the different measures of density for neighbourhood i. We start by considering the logged measure of urban density ($Urb.Den_i$), before distinguishing between its two components, the log of residents ($Res.Den_i$) and workers counts ($Wrk.Den_i$) per hectares of land size.

We include controls for a number of neighbourhood characteristics in X_i. First, we consider the proportions of residents under 18 years old and of residents over 65 years old, to control for propagation of the virus through schooling, and a proxy for the relevance of vulnerable individuals in the area. Second, we take into account several indicators of the socioeconomic characteristics of the neighbourhood. We include the share of white ethnicity, given the evidence of a disproportionately negative impact of COVID-19 on ethnic minorities in terms of both health (McLaren 2021) and economic outcomes (Montenovo *et al.* 2022). In addition, we control for the level of house crowding measured as resident population divided by the residential build-up area, to explain structural drivers of contagion within households (Almagro and Orane-Hutchinson 2022). Moreover, we include the neighbourhood deprivation score, measured by the 2019 English index of multiple deprivation, and its quadratic term to control for the possibly non-linear relationship between the socioeconomic status of a neighbourhood and the incidence of COVID-19 (Morrissey *et al.* 2021). Third, we control for the logged level of particulate matter (PM2.5) pollution to take into account the role of pollution in facilitating the spread of the virus (Travaglio *et al.* 2021). We also include the number of care beds available in the neighbourhood plus one to proxy for the contagion originating from keyworkers operating in nearby high-risk workplaces, such as care homes and hospitals (Alacevich *et al.* 2021). Finally, we control for the cumulative number of COVID-19 cases in other neighbourhoods within the same LAD weighted by the pair-distance between neighbourhoods, which takes into account spillovers from nearby areas (Cole *et al.* 2020).

We also control for variation due to a number of unobserved factors. We control for unobserved, time-invariant heterogeneity at the local government level by including local authority fixed effects θ_r. This allows us to control for important factors that vary at the local government level, such as public health initiatives, and may have a non-parametric relationship with the spread of COVID-19.[7] Residual neighbourhood-varying observable factors are included in the term e_i. Thus the coefficient of interest, α_1, is identified from the within-city neighbourhood variation in urban, resident and worker densities prior to the pandemic.

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 (5) by decomposing the residential (r) working population in a neighbourhood i into resident homeworkers ($hw_i^r = HW_i^r/N_i^r$) and keyworkers ($kw_i^r = KW_i^r/N_i^r$) scaled by the number of residents. 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 ($hw_i^w = HW_i^w/N_i^r$) and employed keyworkers ($kw_i^w = KW_i^w/N_i^r$) per capita. We account for the distribution of the resident and worker populations across these different employment types in our regression analysis as follows:

$$COVID_i = \alpha_1 \log(Res.Den_i) + \alpha_2 hw_i^r + \alpha_3 kw_i^r + \beta_1 \log(Wrk.Den_i) + \beta_2 hw_i^w + \beta_3 kw_i^w + X_i' \Gamma + \theta_r + e_i. \quad (6)$$

Since we control already for the resident and worker densities, the coefficients $\alpha_2 - \alpha_3$ ($\beta_2 - \beta_3$) reflect the change in COVID-19 reported cases per 1000 people from a one unit increase in the number of residents (workers) keyworkers or homeworkers per capita. We include the same control variables and fixed effects as in our baseline specification.

5 | RESULTS

5.1 | Baseline analysis

We start in Table 1 with our baseline model by analysing the effect of urban, resident and worker densities on the spread of COVID-19 cases. Column (1) follows equation (5) in considering the overall measure of urban density. Column (2) differentiates between residents and workers densities. Column (3) reports the results of regression model (6), in which we also consider the composition of resident and worker keyworkers and homeworkers at the MSOA neighbourhood level.

In column (1) of Table 1, controlling for neighbourhood characteristics and local-authority-level time-invariant factors, urban density is significant in explaining the cross-neighbourhood difference in COVID-19 cases, but is small in magnitude. A 1% increase in urban density is associated with 0.005 more reported cases per 1000 (0.3% relative to the mean). We report similar results in column (2). The estimated coefficient for resident density is positive and significant, but small in magnitude, while the coefficient for worker density is negative but not statistically significant. In column (3), which reports estimates for equation (6), accounting for neighbourhood labour composition, worker and residential densities are both statistically significant, however, still very small in magnitude. A 1% increase in residential density is associated with an increase of 0.013 reported COVID-19 cases per 1000 people, while a 1% increase in worker density is associated with a 0.016 decrease in reported COVID-19 cases per 1000. It is particularly interesting that we find an effect for worker density when we consider that a recorded COVID-19 case corresponds to the infected person's neighbourhood of residence.[8] These estimates are consistent with previous studies based on standard measures of population density (Wong and Li 2020; Allcott *et al.* 2020; Desmet and Wacziarg 2022; Almagro and Orane-Hutchinson 2022) and research on manufacturing employment density (Ascani *et al.* 2021a).

Results in column (3) of Table 1 show that the estimated coefficients for the local labour force composition of residents and workers are statistically significant and economically meaningful. A 10 percentage point increase in resident keyworkers, rather than non-essential workers, is associated with 3.15 more COVID-19 cases per 1000 people (a 4.8% increase relative to the mean). In contrast, a 10 percentage point increase in resident homeworkers, rather than non-essential workers, is associated with a decrease of 7.74 COVID-19 cases per 1000 people (a 11.8% decrease relative to the mean). These estimates are consistent with a greater concentration of residents working from home slowing down the infection, preventing the spread of the virus through their place of work to the place where they live. The opposite holds in the case of resident keyworkers, who kept working on site through the pandemic.

We find results that are similar in sign, but smaller in magnitude, for the composition of workers in a neighbourhood. A 10 percentage point increase in keywork employment, rather than non-essential workers, is associated with an increase of 1.46 reported cases per 1000 people, while

TABLE 1 Relationship between urban, resident and worker densities, neighbourhood labour structure, and COVID-19 cases rate by MSOA.

	COVID-19 cases (per 1000 people)		
	(1)	(2)	(3)
Urban density	0.504**		
	(2.57)		
Resident density		0.498*	1.363***
		(1.73)	(3.57)
Worker density		−0.0847	−1.635***
		(−0.26)	(−3.47)
KW resident rate			31.54**
			(2.51)
HW resident rate			−77.35***
			(−13.29)
KW worker rate			14.58***
			(5.08)
HW worker rate			−1.694***
			(−2.71)
Share elderly	−7.216	−8.283*	−31.12***
	(−1.55)	(−1.68)	(−5.27)
Share children	4.699	3.699	−9.370
	(0.43)	(0.33)	(−0.88)
Share white	−31.17***	−31.44***	−28.69***
	(−13.31)	(−13.10)	(−11.49)
House crowding	9.801***	9.659***	4.486***
	(6.51)	(6.29)	(3.25)
Deprivation score	70.13***	70.11***	16.84***
	(16.72)	(16.68)	(3.13)
Deprivation score squared	−76.48***	−76.35***	−38.54***
	(−13.49)	(−13.44)	(−6.46)
Pollution	4.069***	4.121***	4.708***
	(10.07)	(10.17)	(11.96)
Cases spatial lag	0.174***	0.175***	0.250***
	(2.82)	(2.84)	(4.03)
Number of care beds	0.0385***	0.0387***	0.0404***
	(19.87)	(19.71)	(20.90)
LAD fixed effects	Yes	Yes	Yes
Observations	6789	6789	6789
R^2	0.825	0.825	0.835

Notes: The dependent variable is the MSOA-level cumulative number of COVID-19 cases per 1000 people. Urban, resident and worker densities are in log form. Keyworker and homeworker rates for residents and workers calculated over total population in the MSOA. All other control variables measured as previously indicated. Robust standard errors clustered at the MSOA level. T-values reported in parentheses.
*, **, *** indicate $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

a 10 percentage point increase in employment that can be done remotely reduces reported cases in the residential population by 0.17 cases per 1000 people. This is consistent with keyworkers continuing to work on site during the lockdown period, potentially spreading the virus among the local residents, while both homeworkers and other workers largely did not go into work during this time.

Estimated coefficients corresponding to the control variables are largely significant and in line with previous studies. For example, neighbourhoods with more residents per house experienced higher COVID-19 rates, while neighbourhood deprivation displays a hump-shape relationship with COVID-19 rates.

5.2 | Additional analysis

We explore some potential mechanisms at play in linking the labour composition of neighbourhoods with the spread of the COVID-19 virus by performing several additional analyses. We first look at the dynamics of the virus spread by estimating a version of equation (6) by monthly prevalence of reported cases. We then look at the heterogeneity of our main results according to neighbourhood deprivation, followed by an analysis of the role that might be played by occupation type within keywork and homework jobs.

5.2.1 | Dynamic and lockdown analysis

We start by looking at the dynamics of the spread of COVID-19 over the first year. We run the following regression separately for each month m:

$$\begin{aligned} COVID_i^m = {} & \alpha_1^m \log(Res.Den_i) + \alpha_2^m hw_i^r + \alpha_3^m kw_i^r \\ & + \beta_1^m \log(Wrk.Den_i) + \beta_2^m kw_i^w + \beta_3^m kw_i^w + X_i' \,\Gamma^m + \theta_r^m + e_i^m, \end{aligned} \tag{7}$$

where $COVID_i^m$ is the number of reported cases per 1000 in neighbourhood i and month m. In practice, this is estimated as a series of 14 equations, one for each month in our data. The coefficients of interest—α_2^m, α_3^m, β_2^m and β_3^m—are reported in Figure 5. Unlike the estimates from equation (6), which look at the stock of reported cases over the year, equation (7) looks at the flow of reported cases for a given month.

In Figures 5(a) and 5(c), we report results for keyworkers, while results for homeworkers are reported in Figures 5(b) and 5(d). To ease comparability, all estimates are reported as standardized beta coefficients. We observe clear differences in the relationship between resident and worker local labour structures and cases during lockdown periods (March to July 2020, and November 2020 to April 2021) and during the open period (July to November 2020). In particular, cases are significantly higher in neighbourhoods with more resident keyworkers during lockdown periods. This is consistent with keyworkers, who worked on site throughout the pandemic and were thus more exposed to contagion risk, becoming significant drivers of viral transmission in the neighbourhoods where they reside. Interestingly, we observe a negative effect for resident keyworkers during the relaxation of lockdown restrictions (July to November 2020). This may reflect greater precautions taken by keyworkers which, absent lockdown restrictions, provided them with greater protection from the virus compared to other workers, as suggested by Brandily *et al.* (2021). The effect may also be due to the greater social interaction over this period associated with certain jobs in the omitted reference group, that is, non-essential on-site workers in the hospitality and retail industry (see Appendix Table A1). In fact, previous studies have shown how the publicly subsidized 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 2022). The effects are smaller and

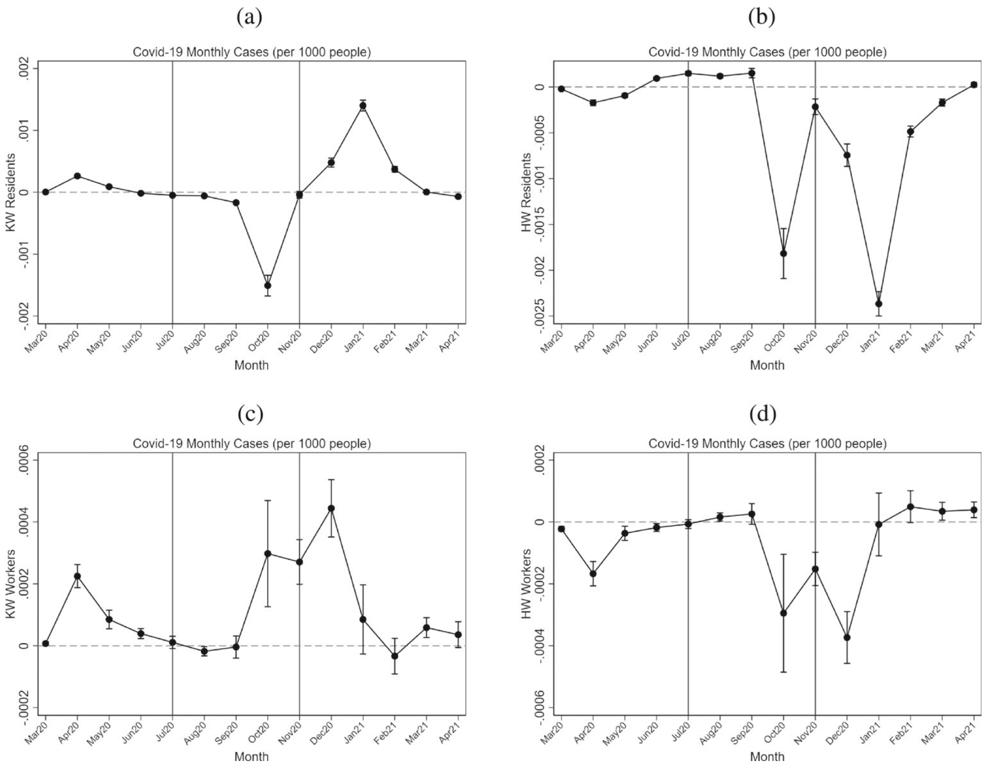


FIGURE 5 Dynamic relationship between neighbourhood labour structure and COVID-19 monthly cases. *Notes*: Beta coefficients reported with 95% confidence intervals. Different regression run for each month. Vertical solid lines show the end of the first national lockdown (4 July 2020) and the beginning of the second national lockdown (5 November 2020). Regressions control for local authority fixed effects, resident and worker densities, dependent children (% of population), elderly (% of population), white ethnicity (% of population), house crowding, deprivation score, PM2.5 pollution, distance-weighted cases within the local authority, and log number of care beds in the MSOA.

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 very small effects in the following months.[9] We find opposite patterns for residents and workers 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.

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 working from home 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 may yield important asymmetries in the distributional impact of the public health measures introduced by many governments in their efforts to stop the spread of viral infections.

5.2.2 | Deprivation heterogeneity

Regression results in Table 1 suggest a non-linear relationship between neighbourhood deprivation and COVID-19 cases. Here, we explore this relationship further by allowing our baseline results to differ by levels of neighbourhood deprivation. This analysis will help us to identify if the relationship between local labour market composition and the spread of the virus is mediated by the level of deprivation of the neighbourhood, particularly when the spatial distribution of keyworkers is clustered around deprived areas.

To do this, we estimate equation (6) including interactions between our key variables—residents' and workers' employment structure—with the four quartiles of the deprivation score distribution.[10] Our results, reported in Figure 6, show evidence of significant neighbourhood heterogeneity. The resident keyworkers share in a neighbourhood significantly increases the incidence of COVID-19 cases only in the most deprived MSOAs (third and fourth quartiles). In contrast, the resident homeworkers share significantly reduces infections in all neighbourhoods, but with a much larger magnitude in the least deprived areas (first quartile). We also find evidence of heterogeneous effects for the neighbourhood employment structure of workers. The share of keyworkers working in a neighbourhood is associated with a higher incidence of COVID-19 in all but the lowest deprivation neighbourhoods. This could arise due to a lower degree of mingling between keyworkers and residents in the lowest deprivation areas. Surprisingly, homeworkers employed in affluent neighbourhoods are positively associated with

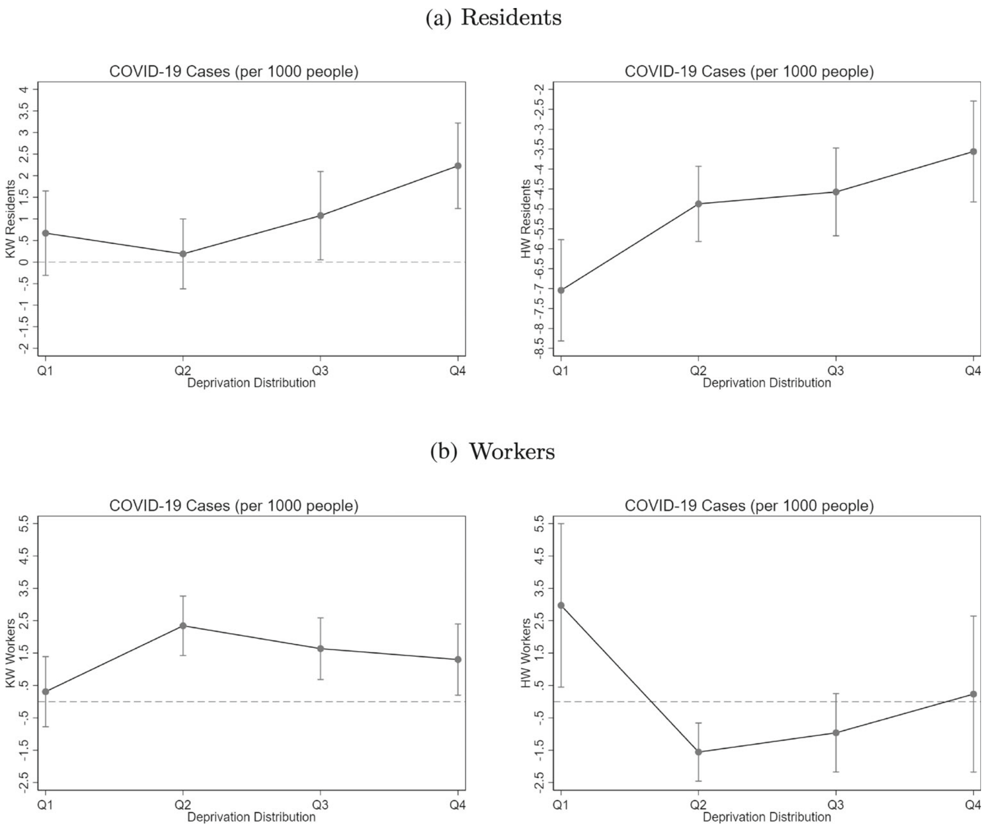


FIGURE 6 Relationship between neighbourhood labour structure and COVID-19 cumulative cases across the neighbourhood deprivation distribution. *Notes*: Neighbourhood deprivation distribution reported from least deprived (Q1) to most deprived (Q4) MSOAs. Neighbourhood deprivation quartiles interacted with employment structure and with density variables. Deprivation control variables replaced with deprivation quartile dummies. Beta coefficients reported with 95% confidence intervals. Regressions control for local authority fixed effects, resident and worker densities, dependent children (% of population), elderly (% of population), white ethnicity (% of population), house crowding, PM2.5 pollution, distance-weighted cases within the local authority, and log number of care beds in the MSOA.

local COVID-19 cases, although the coefficient in this case is estimated imprecisely with large standard errors.

We further look at how these heterogeneous effects change according to lockdown restrictions, reproducing our deprivation quartile estimates for the lockdown periods (March to May 2020, and from November 2020) and the no-lockdown period (July to October 2020). These results are reported in Figure 7. Consistent with the results reported in Figure 5, we find that the effect of resident keyworkers share is negative when lockdown restrictions are lifted, but positive during lockdown periods (Figure 7(a)). The positive effect during the lockdown period is largest for the most deprived areas. Similarly, the negative effect of the share of homeworking residents is greater during lockdown periods, and larger in magnitude for the least deprived neighbourhoods. Results for employees working in the neighbourhood do not differ significantly according to lockdown restrictions (Figure 7(b)), and generally follow the same patterns observed in Figure 6. The only exception to this is resident homeworkers in the least deprived areas, where we see a difference between lockdown and no-lockdown effects.

Overall, these results point to the existence of trade-offs in the introduction of national lockdowns. These public health policies shield people who can work from home, and

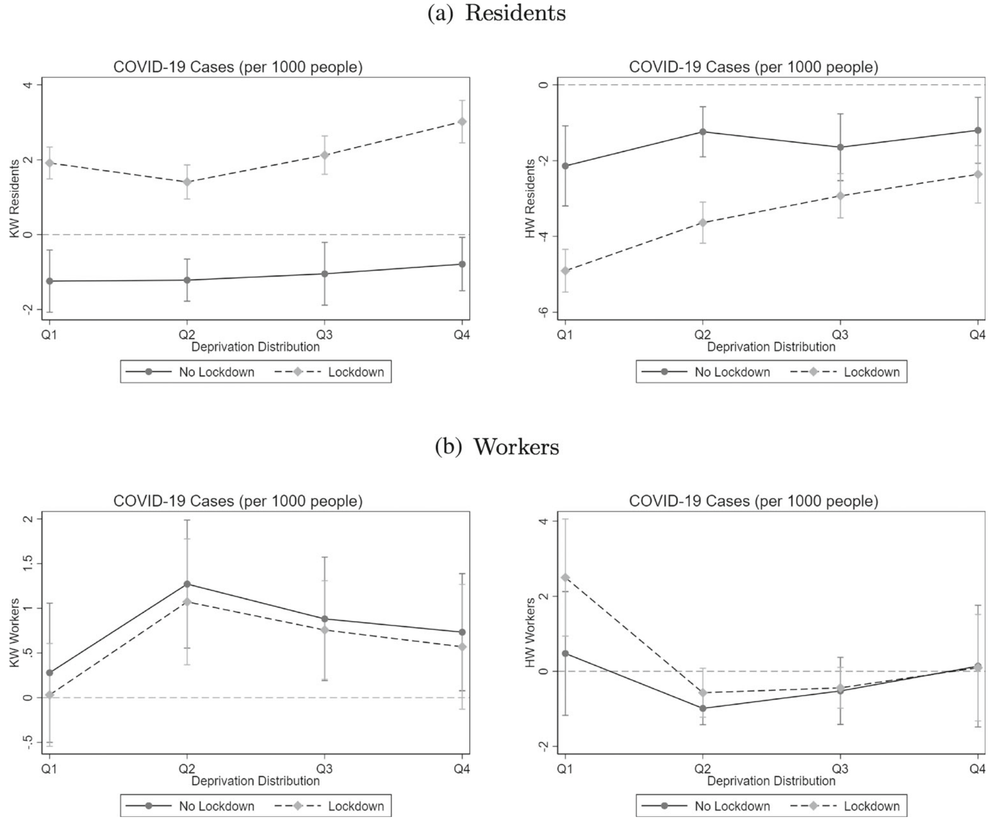


FIGURE 7 Relationship between neighbourhood labour structure and COVID-19 cumulative cases across the neighbourhood deprivation distribution during lockdown periods. *Notes*: Neighbourhood deprivation distribution reported from least deprived (Q1) to most deprived (Q4) MSOAs. Lockdown periods considered are March–May 2020, November 2020, and January–April 2021. Beta coefficients reported with 95% confidence intervals. Regressions control for local authority fixed effects, resident and worker densities, dependent children (% of population), elderly (% of population), white ethnicity (% of population), house crowding, deprivation score, PM2.5 pollution, distance-weighted cases within the local authority, and log number of care beds in the MSOA.

consequently their communities, but with a larger effectiveness in less-deprived areas. At the same time, these policies may have increased the relative exposure and risk of contagion for keyworkers, with the largest effect in the most deprived areas. This points to the need for alternative approaches and possibly further support for targeted policies reflecting labour composition and deprivation of neighbourhoods, such as improved paid sick leave policy or income support to reduce mobility of sick workers (Chang *et al.* 2021), shifting the focus on protecting keyworkers as well as their communities.

5.2.3 | Skill intensity heterogeneity

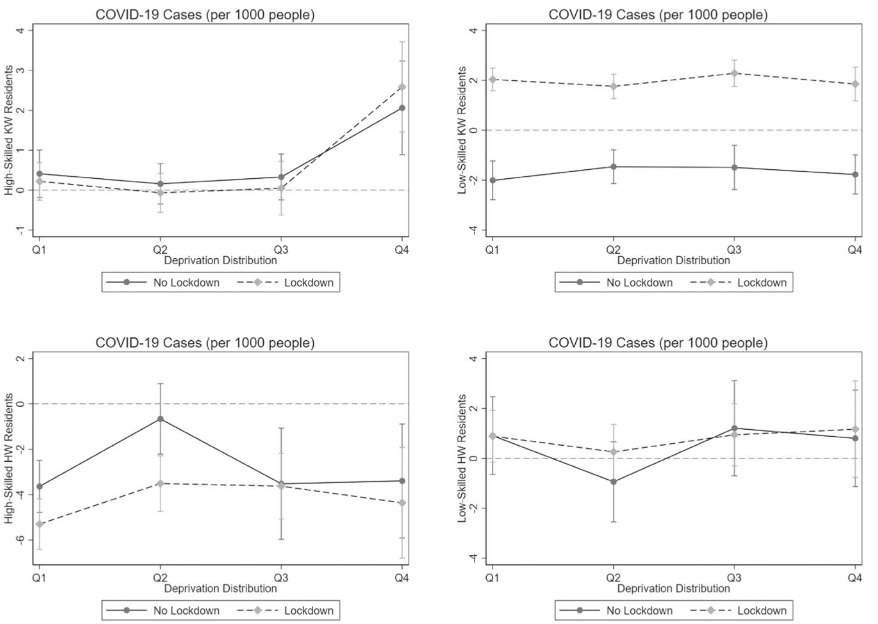
Given the strong heterogeneity in the relationship between keyworkers, homeworkers and viral infection across the deprivation distribution, here we investigate differences in the types of keywork and homework jobs carried out in low- and high-deprivation neighbourhoods. There is indeed a strong relationship between keywork occupation types and neighbourhood deprivation. For example, in low-deprivation neighbourhoods, keywork occupations are largely professional or management, while in high-deprivation neighbourhoods, keywork occupations are more likely to be routine or lower-supervisory (see Appendix Figure A3). Of the five most common keywork jobs, care workers and home carers are much more concentrated in the higher-deprivation neighbourhoods, while secondary education teaching professionals are more concentrated in the lower-deprivation neighbourhoods (Appendix Table A3). Further, the most concentrated keywork occupations differ substantially by deprivation quartile. Over 40% of high-skill jobs (e.g. aircraft pilots, flight engineers, managers, directors, etc.) live in the least-deprived areas, as opposed to less than 10% residing in the most-deprived areas. Conversely, over 40% of people employed in low-skill occupations (street cleaners, food process operatives, hospital porters, etc.) live in the most-deprived neighbourhoods, as opposed to just over 10% in the least-deprived (see Appendix Table A4).

We explore the potential implications for the spread of viral infection of the differences in the distribution of high- and low-skill keywork and homework jobs across neighbourhoods. To do this, we repeat the analysis reported in Figure 7, replacing keywork and homework share variables with high- and low-skill occupation keywork and homework shares. The results of this exercises are reported in Figure 8.

These figures show a number of interesting results. For the resident population, the larger positive effect of keyworkers on COVID-19 cases in high-deprivation, as opposed to low-deprivation, neighbourhoods previously documented comes from two sources. The first is heterogeneity in the effect of high-skilled keyworkers, for whom we see a significant positive effect only in high-deprivation areas. 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 heterogeneity in this effect may be mediated further by a high level of crowding in multi-generational housing, more common in deprived areas; this could have facilitated the spread of the virus from the residents' workplaces to the local community. The second source is that low-skilled keyworkers, for which the estimated positive effect is homogeneous across areas, are more concentrated in higher-deprivation areas (Figure 8(a)). However, it is interesting that we do not find any significant difference for low-skilled resident keyworkers across the deprivation distribution, which is always positive during lockdown periods and negative in other periods.

We find that the negative effect of resident homeworkers is much stronger for high-skilled occupation groups, and the estimated effects, conditional on skill group, are fairly homogeneous across deprivation quartiles (Figure 8(a)). Strikingly, there is no relationship between resident low-skilled homeworkers and the incidence of COVID-19 cases across neighbourhoods. This suggests that the observed difference in the protective effect of homeworkers on virus spread

(a) Residents



(b) Workers

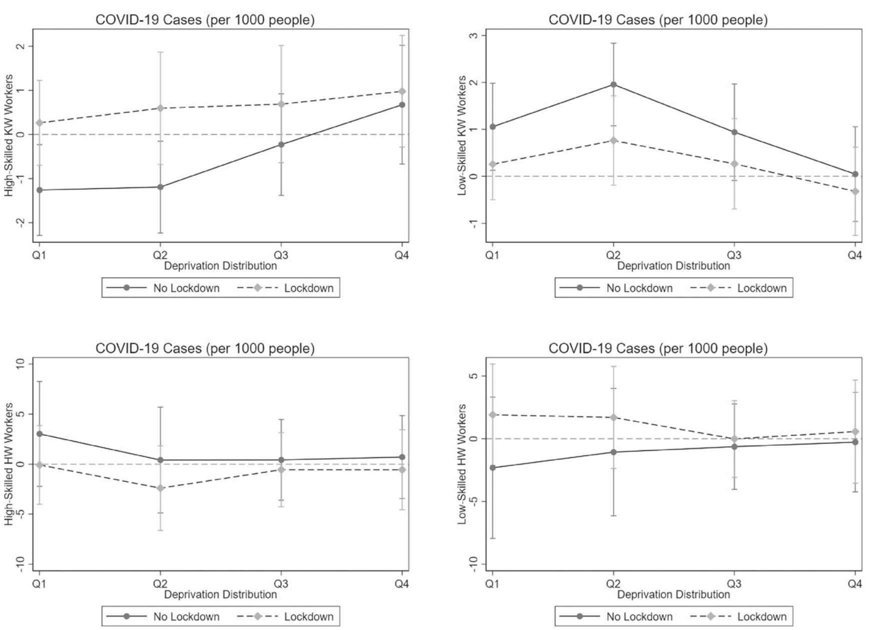


FIGURE 8 Relationship between neighbourhood skilled labour structure and COVID-19 cumulative cases across the neighbourhood deprivation distribution during lockdown periods. *Notes*: Neighbourhood deprivation distribution reported from least deprived (Q1) to most deprived (Q4) MSOAs. Lockdown periods considered are March–May 2020, November 2020, and January–April 2021. Beta coefficients reported with 95% confidence intervals. Regressions control for local authority fixed effects, resident and worker densities, dependent children (% of population), elderly (% of population), white ethnicity (% of population), house crowding, deprivation score, PM2.5 pollution, distance-weighted cases within the local authority, and log number of care beds in the MSOA.

by neighbourhoods is due to the differences in occupational concentrations, with higher-skilled homeworkers being more concentrated in lower-deprivation areas.

When looking at workers (Figure 8(b)), we observe a significant heterogeneity only for high-skilled keyworkers working in deprived areas during lockdown periods, and in the case of low-skilled keyworkers who facilitate the spread of the disease while working in affluent areas during open periods. Estimates for employed homeworkers are very small and imprecisely estimated.

Overall, these findings suggest that the heterogeneity in how keyworkers and homeworkers affect the spread of COVID-19 by neighbourhood deprivation is due to differences in the types of keywork and homework jobs that are done in these neighbourhoods. In particular, low-skill keywork occupations appear to be more susceptible to spreading the virus, particularly during the lockdown period, than high-skilled keywork occupations. This disadvantages higher-deprivation neighbourhoods, which tend to have higher concentrations of keywork in low-skilled versus high-skilled occupations. This evidence further supports the hypothesis that lockdown measures were effective in reducing the spread of the virus through working from home only in affluent neighbourhoods with large shares of resident high-skilled workers.

5.2.4 | Robustness

Equation (6) provides the estimated association between cumulative reported cases and neighbourhood labour composition. Using these estimates to draw conclusions about actual cases in a neighbourhood is potentially challenged by two sources of bias. The first, as with most studies based on observational data, reflects the possibility that the neighbourhood characteristics not included as controls affect the spread of the virus and are correlated with the labour force distribution. To account for this, we have included a number of neighbourhood characteristics in X_i that we believe to be important and as exhaustive as possible. In addition to that, we also control for unobserved time-invariant factors at the local government level by including local authority fixed effects that allow us to control for important factors, such as local public health initiatives. These estimates therefore are based on variation between neighbourhoods within the same local authority.

The second source of bias arises from the fact that our outcome reflects only reported cases. If testing rates differ across groups, as keyworkers may have undergone regular testing and therefore report more, then we may not be able to distinguish between different rates of contraction and different rates of reporting. Notice that because the geographic location of a reported case is linked to the residential location of the infected person, this issue will not affect estimates for the population of workers. Conditioning on neighbourhood characteristics, local authority fixed effects, and the residential occupation distribution, differences across these estimates plausibly reflect differences in the actual contraction of COVID-19 cases in the neighbourhood.

This second source of bias potentially has consequences for what the coefficients for the residential population tell us about actual infections. We address this potential bias in several ways. First, while testing capacity was scarcer and mostly targeted at keyworkers during the first lockdown period (March to June 2020), testing capacity increased significantly later on, with a nationwide campaign of free testing kits for all citizens irrespective of occupation or location promoted by the NHS. Our dynamic analysis in Figure 5 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. This is corroborated in Table C1 of the Online Appendix, where we exclude the weeks from January 2021 onwards 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. In addition, the dynamic analysis also estimates precisely 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. Moreover, we show in Table C2 of the Online Appendix that by using the rate of COVID-19 deaths over 1000 residents as a dependent variable, we reach qualitatively similar results. This is reassuring, as COVID-19 deaths do not suffer from the potential reporting bias as all deceased people were tested for COVID-19. We do not find significant results for the occupation distribution of workers. This is not surprising as deaths are rare relative to cases, and we are likely unable to pick up the secondary effect of virus spread.

We perform several additional sensitivity tests to validate our results, as reported in the Online Appendix. First, we replicate the main estimation using different measurements for the dependent variable, initially considering the cumulative number of COVID-19 cases as dependent variable in a count Poisson model in Table C3, and then using the logged number of COVID-19 cases plus one in a OLS model in Table C4. The results are also consistent when using as an outcome variable the weekly number of COVID-19 cases scaled by 1000 residents in a panel setting in Table C5.

Second, we want to make sure that the density variables used in our analysis are not affected by measurement error bias. In particular, by focusing on workers, we might fail to identify the role of non-resident non-workers moving to a neighbourhood for school, leisure or other activities. To better control for this, and to provide robustness tests for the traditional urban density measures, we adopt the novel approaches seen in the urban economics literature (Henderson *et al.* 2021; 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 use data from the GHS-POP spatial raster dataset on the ambient population distribution averaged over 24 hours per 1 square kilometre cell for each month in 2015 (Schiavina *et al.* 2019) to proxy for overall urban density. Data from the ENACT-POP spatial raster dataset is instead used to capture seasonal nighttime and daytime changes in the number of people per square kilometre in 2011 (Schiavina *et al.* 2020), to distinguish between where people live (proxied by nighttime population) and where people usually are during the day (proxied by daytime population). Within-city spatial distribution of these variables can be seen in Figure C1 of the Online Appendix, and results reported in Table C6 using the log average measure of monthly daytime, nighttime and overall satellite densities are consistent and corroborate our main results.

In addition, in Table C7 of the Online Appendix we look at the relationship between population, employment density, neighbourhood labour structure, and COVID-19 cases by distinguishing between MSOAs in small and large Travel To Work Area (TTWA) commuting areas. This analysis further informs 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. Results shown in Table C7 seem to indicate that resident density seems to matter more in neighbourhoods that are part of smaller commuting areas, while worker distribution is much more relevant in neighbourhoods that are part of larger commuting areas. Moreover, in Table C8, we also repeat the baseline analysis using only data on the employment and population structure of neighbourhoods from the 2011 UK Census, yielding very similar results.

A final issue with our specification is that the inclusion of local authority fixed effects excludes a significant amount of variation in both COVID-19 cases and labour market composition that exists between different cities. In Table C9 of the Online Appendix, we report the same estimates as reported in Table 1, excluding LAD fixed effects. Three things are worth noting about these results. First, the signs of the estimated effects for labour market composition and density remain unchanged. Second, the magnitudes on our occupational concentration measures (kw^r, kw^w, hw^r and hw^w) show little change when fixed effects are included or excluded. Finally, our coefficient estimates for density are consistent in sign, but significantly larger in magnitude when fixed effects are excluded. These results are consistent with the majority of the variation in our variables of interest coming from within, rather than between, cities. We are confident that the inclusion of fixed effects allows us to abstract from potentially problematic sources of variation, such as differences in local public health policies, without significantly sacrificing other potentially important sources of variation.

With all this in mind, we can safely interpret our coefficients as reflecting the association between neighbourhood labour force distributions and reported COVID-19 cases, confident that these estimates provide valuable information about the actual spread of the virus.

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 neighbourhood labour composition 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 localized nature of the transmission mechanisms of the SARS-CoV-2 virus (Glaeser and Kahn 2004; Sá 2020; Almagro and Orane-Hutchinson 2022), and show that density at the neighbourhood level is a significant factor for transmission.

Second, we 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 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, our findings show that the relationship between labour composition and deprivation level of neighbourhoods is key to understand the link between the increasing evidence suggesting that areas with a large presence of essential occupations and sectors are associated with higher contagion risk, as people keep working on site (Almagro and Orane-Hutchinson 2022) preventing a sharp reduction in their mobility (Ascani *et al.* 2021b), and studies pointing out the relationship between disadvantaged socioeconomic groups and virus contagion (Chang *et al.* 2021). While previous papers have highlighted the role of income distribution across places as a significant element in the COVID-19 pandemic (Desmet and Wacziarg 2022; Rodríguez-Pose and Burlina 2021), we provide novel findings pointing to a significant increase in risk across neighbourhoods in England that are characterized as having a large population of keyworkers residing in the lowest quartile of income distribution, health, and housing deprivation.

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 2022; 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 living and working in deprived areas, and workers who are able to work from home in more affluent neighbourhoods. This suggests that the effect of lockdowns may be somewhat limited at preventing contagion in deprived areas of cities, particularly for the most vulnerable and exposed categories of keyworkers.

While the paper provides novel insights on the relationship between local labour market structures and spatial variation in COVID-19 morbidity, several aspects require further analysis. In particular, future research may connect the heterogeneous effects of occupation and neighbourhood characteristics explored in our analysis with data on individual-level mobility networks, both within and from outside the locality (Almagro *et al.* 2023; Ascani *et al.* 2021b; Chang *et al.* 2021). Connected to this, the role of neighbourhood labour structures should also be analysed taking into account potential disproportionate effects from superspreader events and locations (Almagro *et al.* 2023; Ascani *et al.* 2021b; Chang *et al.* 2021).

Our findings have important policy implications, highlighting significant asymmetries in the distributional impact of public health measures introduced to stop the spread of viral infection. We evidence 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. The increase in spread is driven mainly by 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 mostly in affluent areas with a large number of high-skilled homeworkers. These results highlight that public health interventions focusing solely on reducing mobility, via lockdowns or work-from-home policies, partly shift the relative risk and social and economic burden of viral infections from the affluent neighbourhoods, characterized 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. Alternative or complementary approaches focused specifically on protecting keyworkers as well as their communities may therefore be necessary. These may include improved paid sick leave policies or other public transfers, and support schemes for the most affected workers and households (Basso *et al.* 2022; Chang *et al.* 2021; Aspachs *et al.* 2022).

These results provide important insights on the determinants of diffusion of the virus, with a focus on understanding which areas and group of workers remain more at risk of health consequences and economic loss from the spread 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.* 2022), which accounts for the significant differences in the on-site working arrangements of keyworkers and non-essential workers. We also highlight the relationship between these elements and the increased risks associated with residence in the most-deprived neighbourhoods. By offering novel evidence on 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 people work and live, our analysis can inform the implementation of more effective lockdown and other public health policies targeting more precisely the neighbourhoods that are more vulnerable from both an economic and contagion perspective. These elements are essential to better design policies that prevent further negative economic shocks as well as inequalities in the welfare state (Stantcheva 2022; Aspachs *et al.* 2022). As such, the findings presented provide relevant insights for the design and implementation of more nuanced and socially just policy approaches for large epidemics and future pandemic events.

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ENDNOTES

[1] Neighbourhoods are defined using the ONS Middle Super Output Area (MSOA) nomenclature reflecting on average 7000 residents (3000 residential buildings).

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

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

[4] We also use information on the national-level employment growth between 2011 and 2018 to scale 2011 population counts to 2018 estimates. Details regarding the calculation and definition of the resident and worker types can be found in Appendix A.

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

[6] Summary statistics for all variables used in our analysis are available in Appendix Table A2.

[7] Results are robust to controlling for local labour market idiosyncratic effects, including Travel to Work Area fixed effects.

[8] It is possible that some fraction of the neighbourhood workers are also neighbourhood residents. If such workers are driving the worker density spread of COVID-19, then we would not expect to see a significant relationship once we have controlled for residential density.

[9] 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.

[10] Specifically, in addition to interacting with employment structure, we also interact deprivation quartile dummies with density variables, and replace the deprivation variables in equation (6) with deprivation quartile dummies.

[11] Occupations are defined by four-digit and three-digit Standard Occupational Classification (SOC) codes. The 369 four-digit codes nest the 90 three-digit codes.

[12] Labelled dataset EMP04: Employment by occupation, available online at https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/employmentbyoccupationemp04 (accessed 21 March 2024). These are the latest pre-pandemic data for which employment estimates by four-digit occupation codes are available.

[13] 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 is available at ONS (2020).

[14] We construct the industry weights using information from the January 2017 to January 2020 waves of the UK Quarterly Labour Force Survey. The weight for occupation o_4 and industry s reflects the proportion of o_4 jobs that are in industry s.

[15] This is question 48 of the individual questionnaire for England. This question is asked only of respondents who report having done paid work in the last 12 months.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A. CALCULATION OF RESIDENT AND WORKER TYPES

Population estimates by occupation are based on information from the 2011 population census for England. For each neighbourhood, we observe the number of residents employed in each of 369 occupations, and the number of workers employed in each of 90 occupations.[11] For the main analysis, we want to scale these data to reflect employment population counts as they where at the beginning of the pandemic. In the first step, we use a procedure similar to that of a Bartik shift–share to scale the 2011 population counts to reflect 2018 estimates. In the second step, we assign occupations to one of keyworker (KW), homeworker (HW) or other (OW).

A.1 Step 1: scaling population counts

We use information on aggregate UK employment, for each of the 369 four-digit occupation codes, to scale the 2011 census population estimates to 2018 levels. Aggregate population estimates are provided by the ONS.[12] For each four-digit occupation code, denoted by o_4, we calculate the percentage change in aggregate employment between 2011 and 2018 as

$$\Delta N_{o_4} = \frac{N_{o_4,2018} - N_{o_4,2011}}{N_{o_4,2011}},$$

where $N_{o_4,t}$ is the aggregate number of employees in occupation o_4 in year t.

We use ΔN_{o_4} to scale neighbourhood employment from 2011 to 2018 levels. Specifically, the residential population count for neighbourhood i and occupation o_4 is calculated as

$$N^r_{i,o_4,2018} = N^r_{i,o_4,2011} \times \Delta N_{o_4},$$

where $N^r_{i,o_4,2011}$ is the census count of residents in neighbourhood i who work in occupation o_4. To keep the notation simple, we drop the year subscript on $N^r_{i,o_4,2018}$ for the remainder of this paper.

We repeat the exercise for estimating the 2018 distribution of workers by place of work. The only difference is that instead of the four-digit occupation codes, we use the 90 three-digit (minor group) SOC codes, which are publicly available for the 2011 census.

A.2 Step 2: assigning occupations to work type

Here, we describe the procedure for calculating the number of keyworkers and homeworkers using $N^r_{i,o_4,2018}$, as calculated above. A keywork job reflects a job that likely would have continued to be done on site throughout the first year of the pandemic. We identify this using the classification from the 'Key workers reference tables' (ONS 2020), which classify each occupation and industry pair as being either keywork or not.[13] We use these classifications to create a keyworker index for each occupation code, denoted by $kw_{o_4} \in \{0, 1\}$, which reflects the proportion of jobs in occupation o_4 that are keywork. For an occupation o_4, kw_{o_4} is calculated as the weighted average of all values in the 'Key workers reference tables', where the weights reflect the national representation of each industry within the occupation.[14]

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 follows the work of Dingel and Neiman (2020), and reflects the proportion of work in each occupation that can be done from home. Combining these two pieces of information with the employed population counts, we calculate the number of residents who are employed in keywork occupations that require being on site,

$$KW^r_i = \sum_{o_4} N^r_{i,o_4} \times kw \times \left(1 - h_{o_4}\right),$$

and the number of residents in jobs that can be done from home,

$$HW_i^r = \sum_{o_4} N_{i,o_4}^r \times h_{o_4}.$$

To calculate the numbers of each type of worker who work in each neighbourhood, we must recalculate the indexes to reflect the 90 three-digit SOC occupation codes for each of the keywork and homework indices, which we denote as kw_{o3} and h_{o3}. The three-digit index is the weighted average of all four-digit indices, where weights reflect the contribution of each o_4 to total employment in o_3. Weights are calculated from the Quarterly Labour Force Survey (all waves from January 2017 to January 2020). Based on this, the number of keyworkers who work in neighbourhood i (and must work on site) is calculated as

$$KW_i^w = \sum_{o_3} N_{i,o_3}^w \times kw_{o_3} \times \left(1 - h_{o_3}\right),$$

and the number of homeworkers who work in neighbourhood i is

$$HW_i^w = \sum_{o_3} N_{i,o_3}^w \times h_{o_3}.$$

A.3 Calculating the other workers

In our analysis, we also want to account for workers who hold jobs that must be done on site, but are not keyworkers. We refer to these as *other workers*, denoted by OW, where OW is calculated as the difference between total employees (by place of residence or place of work) and the sum of keyworkers and homeworkers:

$$OW_i^r = N_i^r - HW_i^r - KW_i^r$$

and

$$OW_i^w = N_i^w - HW_i^w - KW_i^W.$$

A.4 Matching estimates to reported working from home

The 2011 UK census data include an important feature that makes them uniquely suitable for this study. The census is the only pre-pandemic data source for which we can observe the occupation-specific distribution of workers by place of work and place of residence at a granular geographic level. Other data sources provide estimates of this distribution by place of work (e.g. the Business Structure Database), but not residence.

An alternative data source would be the 2021 census. However, the 2011 census is better suited than the 2021 census for this study, for two important reasons. First, the 2021 census was conducted during the second national lockdown. This may give rise to concern about endogenous movements of the labour force (i.e. changing work or residence *because* of the spread of COVID-19). Second, it is unclear how census questions regarding place of work were responded to in 2021. The census questions where not modified to account for the national lockdown. Therefore questions regarding where respondents work may have been handled differently by different people. For example, we show below that a very high proportion of census respondents stated that their main place of work is at home. We therefore cannot use these data to count reliably the number of workers who work in a given neighbourhood.

We can use information from the 2021 census to get a sense of the accuracy of our homework measure in capturing variation across neighbourhoods in the potential for remote working. For

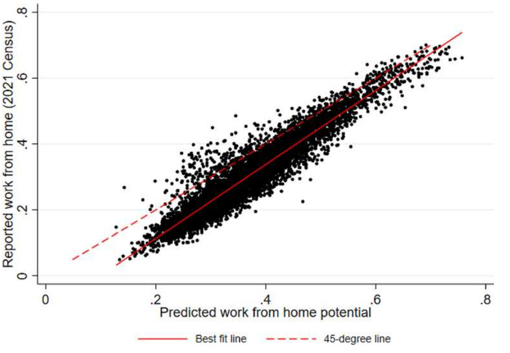

FIGURE A1 Matching work-from-home estimates to 2021 population census. *Notes*: This figure shows a scatterplot of estimated work-from-home potential rates for each neighbourhood against the proportion of respondents who state that they *work mainly from home* in the 2021 UK population census. The red line is plotted at 45°. We exclude 121 neighbourhoods for which the geographic boundary was changed between the 2011 and 2021 censuses.

each neighbourhood, we calculate the proportion of census respondents who stated that they ‘work mainly at or from home’ for the question: ‘How do you usually travel to work?’[15] While this provides us with some guidance as to how many jobs can be done from home in a neighbourhood, there are two reasons why we should not expect it to correspond exactly to our estimated work-from-home rate, HW_i^r/N_i^r. First, our rate is meant to reflect the maximum number of jobs that can be done from home. Some workers in a job that can be done from home will have continued to go into the office during the national lockdown. Second, as mentioned above, there may be differences across census respondents in whether they interpret the question as referring to work during the lockdown period or outside of the lockdown period. The census did not provide any guidance for this. For these reasons, we would expect our measure to be, on average, higher than what we estimate from the census. Nonetheless, if our measure captures some useful information, then we expect to see a high correlation. In Figure A1, we plot the census reported working from home against our predicted working from home potential. As expected, on average we predict a higher proportion of homeworking than does the census, but the correlation, equal to 0.940, is very strong.

APPENDIX B. SUMMARY STATISTICS

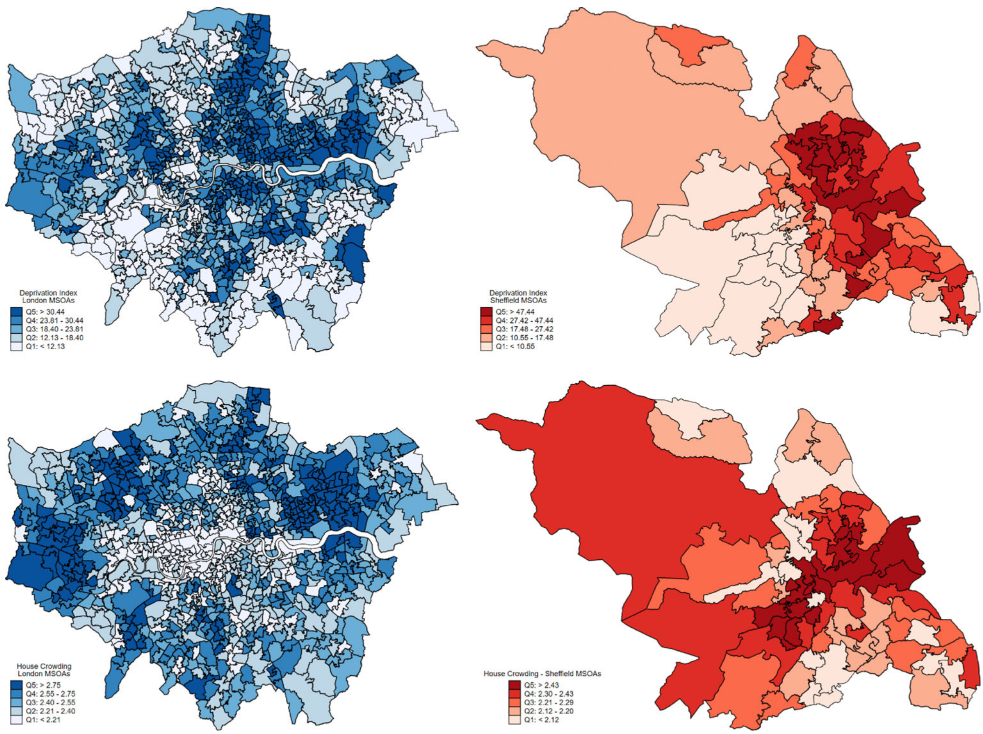

FIGURE A2 Deprivation and house crowding index across MSOAs within the Greater London Authority and Sheffield Local Authority. *Notes*: Figures are based on ONS data for 2018.

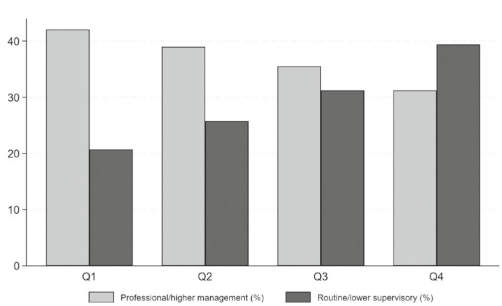

FIGURE A3 Proportion of keywork by occupation type and neighbourhood deprivation. *Notes*: Neighbourhood deprivation distribution reported from least deprived (Q1) to most deprived (Q4) MSOAs. Occupation classification according to the ONS socioeconomic classification (variable NSECM10).

TABLE A1 Selected occupations by allocation into work types.

Keywork occupations		Homework occupations		Other occupations	
SOC	Description	SOC	Description	SOC	Description
1181	Health services and public health	1115	Chief executives	1221	Hotel and accommodation managers
1211	Managers/proprieters in agriculture	1116	Elected officers	2451	Librarians
1242	Residential care management	1131	Financial managers and directors	2452	Archivists and curators
2211	Medical practitioners	1134	Advertising and public relations	3414	Dancers and choreographers
2213	Pharmacists	1135	Human resource managers	3415	Musicians
2215	Dental practitioners	1136	IT and telecom directors	3441	Sports players
2216	Veterinarians	1150	Financial institution managers	3442	Sports coaches and instructors
2217	Medical radiographers	1190	Managers and directors in retail	3443	Fitness instructors
2218	Podiatrists	1226	Travel agency managers	3565	Inspectors of standards
2219	Health professionals	1255	Waste disposal and environmental	5112	Horticultural trades
2221	Physiotherapists	1259	Managers 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 managers	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	Skilled 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	Senior 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

TABLE A1 (Continued)

Keywork occupations		Homework occupations		Other occupations	
SOC	Description	SOC	Description	SOC	Description
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 assistants	3538	Financial accounts managers	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 government 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 tables' (ONS 2020). 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 categorized in the other two typologies.

TABLE A2 Summary statistics for main COVID-19 and neighbourhood labour structure variables in our estimation sample.

	Mean	S.D.	Min	Max
COVID-19 cases (per 1000 people)	65.622	24.504	6.183	198.961
Urban density	2.938778	1.275497	0.052097	6.127545
Resident density	2.956435	1.274204	0.054571	5.65055
Worker density	2.127944	1.162783	0.025504	7.185164
KW resident rate	0.108516	0.020703	0.025824	0.29826
HW resident rate	0.193619	0.071919	0.044038	0.57216
KW worker rate	0.103995	0.106653	0.016258	3.240652
HW worker rate	0.180879	0.550636	0.017712	36.08404
High-skilled KW resident rate	0.030706	0.010744	0.009056	0.189719
Low-skilled KW resident rate	0.07781	0.015443	0.015369	0.149532
High-skilled HW resident rate	0.108961	0.044345	0.019638	0.322758
Low-skilled HW resident rate	0.084658	0.028359	0.022605	0.280774
High-skilled KW worker rate	0.02969	0.038041	0.004352	1.396916
Low-skilled KW worker rate	0.074305	0.072515	0.011494	1.843736
High-skilled HW worker rate	0.0974	0.312282	0.008399	20.39893
Low-skilled HW worker rate	0.083479	0.239092	0.008665	15.6851
Share elderly	0.187825	0.069258	0.00539	0.527562
Share children	0.19097	0.039274	0.015736	0.381848
Share white	0.863379	0.179995	0.056242	0.995686
House crowding	2.299516	0.286755	1.031233	5.181376
Deprivation score	0.248642	0.152174	0.02542	1
PM2.5 pollution	9.399321	1.681159	4.217815	13.74315
Cases spatial lag	36.78145	71.47233	0	974.8117
Number of care beds	67.44813	73.22258	0	803

Notes: Summary statistics for variables defined in Section III, reported for the main estimation sample.

TABLE A3 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 five keywork occupations by percentage of all keywork, the concentration of occupations according to neighbourhood deprivation. Each cell reports the occupation by percentage of all keywork in the corresponding neighbourhood. UK SOC codes reported in parentheses.

TABLE A4 Most concentrated keywork occupations by neighbourhood deprivation.

Occupation	Deprivation quartile			
	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 percentage of jobs in the corresponding occupation that are in each deprivation quartile. UK SOC codes reported in parentheses.