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Filipa Sá

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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JEL Classification: I18

Keywords: COVID-19, lockdown, occupation

Filipa Sá - filipa.sa@kcl.ac.uk
Kings College London and CEPR

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Filipa Sá†

November 10, 2021

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†King's Business School, King's College London, Bush House, 30 Aldwych, London, WC2B 4BG, United Kingdom. Other affiliations: IZA, CEPR and LSE Centre for Macroeconomics. Email: filipa.sa@kcl.ac.uk.

1 Introduction

Many governments have used non-pharmaceutical interventions — lockdowns — to reduce the spread of SARS-CoV-2, the virus that causes Covid-19. Lockdowns include different measures, such as stay-at-home orders, restrictions on social gatherings and business closures. The main challenge in estimating the effects of lockdowns is the difficulty in constructing a meaningful counterfactual scenario: what would have happened in the absence of the lockdown?

I study the effects of national lockdowns on Covid-19 infections and mortality in England. There have been three national lockdowns in the UK. The first national lockdown was announced on March 23, 2020 and started being eased on June 1, 2020. The second national lockdown was in place for only four weeks, during November 2020. The third national lockdown started on January 6, 2021 and was gradually eased from March 8, 2021. All these lockdowns imposed stay-at-home orders, closed hospitality venues, gyms, indoor leisure facilities and non-essential retail and imposed restrictions on social gatherings. Schools were closed during the first and third lockdowns, but remained open during the second lockdown. During all three lockdowns, essential sectors — health, essential retail, transport, manufacturing and construction — were allowed to remain open.

Although lockdowns are national in scope, their impact on a given local area depends on the type of occupation. Local areas with a larger share of employment in occupations closed by lockdown are more exposed to the national lockdowns. Local areas where most residents are keyworkers in essential sectors are less exposed to the national lockdowns. I work with a fine level of geographic disaggregation and use data by Middle Layer Super Output Area (MSOA). There are $6,789$ MSOAs in my data, with an average population of $8,000$ people. These MSOAs are aggregated into 324 local authorities. My research design constructs control and treatment groups using cross-sectional variation across MSOAs in the share of employment in occupations closed by lockdown. The model controls for the share of employment in occupations that cannot be done from home and require high proximity to others — labeled as non-homeworking and high proximity (NHHP) — and compares local areas where most of these occupations are in sectors closed by lockdown with local areas where most of these occupations are in sectors allowed to remain open.

It is difficult to examine the effect of the first lockdown on infections, because at that early stage in the pandemic Covid-19 tests were only administered to patients admitted to hospital, so there are no data on the actual number of infections. My analysis of the effect on infections therefore focuses on the second and third national lockdowns. When studying the effect on mortality, I analyse all three national lockdowns.

I find that the lockdowns reduced infection and mortality rates. The second lockdown had a larger effect on infection rates than the third lockdown. For mortality, the first lockdown and second lockdowns had a larger effect than the third lockdown. A tier system of local restrictions was already in place before the third lockdown, so the incremental effect of this lockdown is smaller. I find that an increase in the share of employment in NHHP occupations that were closed during lockdown from 28% to 36% — corresponding to the bottom and top quintiles of the distribution of this share — would have reduced weekly infections by 78 cases per 100,000 people during the second lockdown and would have reduced monthly mortality by 3 deaths per 100,000 people during the first and second lockdowns. These are sizeable effects. Compared to a mean value of 119 weekly infections per 100,000 people and 15 monthly deaths per 100,000 people, the infection rate would have fallen by 66% and the mortality rate would have fallen by 20%.

The causal interpretation of these results relies on the identification assumption of common trends — in the absence of lockdown, the evolution of Covid-19 infections and mortality in local areas with a larger share of employment in occupations closed by lockdown would have been the same as in local areas that had a similar share of employment in NHHP occupations, but where most of these occupations remained open during lockdown. To test the robustness of the main results, I divide local areas into percentiles of the share of employment in NHHP occupations that were closed during lockdown. I then estimate the model for infections including linear trends specific to each of these percentiles. I find that the results are robust to the inclusion of these MSOA percentile-specific trends.

One challenge in using variation in occupation shares across MSOAs to estimate the effects of lockdowns is that MSOAs with a large share of employment in NHHP occupations that were closed during lockdown — primarily, hospitality, entertainment and non-essential retail — differ on characteristics that could affect Covid-19 infection and mortality rates. In particular, high exposure MSOAs tend to be urban areas, with a younger population, a larger share of ethnic minority population, higher population density, higher income and better health. This implies that the estimates may suffer from omitted variable bias. However, my results are robust to the inclusion of controls for these covariates. In addition, the high level of granularity in my data allows me to include local authority fixed effects in the model and further reduce omitted variable bias.

An important caveat of my empirical approach is that it does not capture the aggregate effect of the lockdowns on the entire country. Because my control group are local areas with a large share of keyworkers, if the lockdowns had an aggregate effect on the entire country that did not vary by occupation, my empirical strategy would not detect it. As some lockdown measures affected all local areas regardless of occupation composition — for example, restrictions on social gatherings — my results would underestimate the aggregate effect of the national lockdowns. However, my quasi-experimental approach has the key advantage of reducing selection bias and allowing a causal interpretation of the results, under the identifying assumption that the control group provides a counterfactual for the evolution of Covid-19 infections and mortality rates in the treated group in the absence of treatment.

To further explore the mechanism behind these results, I use Google mobility data to test whether the effects of the national lockdowns on time spent at home differ depending on the occupation composition of local areas. I find that all three national lockdowns increased time spent at home by more in local areas that had a larger share of employment in occupations closed during lockdown. For the first lockdown, I find that an increase in the share of employment in NHHP occupations that were closed during lockdown from the bottom to the top quintile value would have increased the percentage change in time spent at home relative to baseline by 1.4 percentage points. Compared to a mean value of 12, this corresponds to an increase of about 12% in the percentage change in time spent at home.

My study is not the first to examine the effect of lockdown policies on Covid-19 infections and mortality. Born et al. (2021) use synthetic control techniques to develop a counterfactual lockdown scenario for Sweden, one of the few countries not to impose a lockdown. They use a donor pool of European countries to construct a synthetic control that behaves just like Sweden in terms of infections before the lockdown. They find that a 9-week lockdown in the first half of 2020 would have reduced infections and deaths substantially. Two papers examine the effects of lockdowns using data for a panel of countries. Askitas et al. (2021) use daily data and estimate an event-study model. They find that the most effective interventions are cancelling public events, imposing restrictions on private gatherings and closing schools and workplaces. Restrictions on internal movement, public transport and international travel are less effective. Caselli et al. (2021) examine the effectiveness of lockdowns in reducing Covid-19 infections using local projections. They find that lockdowns had a large negative effect on infections, especially if adopted soon after the first Covid-19 case was detected. Goldstein et al. (2021) also use local projections and find that lockdowns reduce the number of Covid-19 cases and deaths, but their effect fades over time because of increasing non-compliance with mobility restrictions.

These papers use country-level data to examine the effect of lockdowns. In contrast, I use data for small local areas in England and adopt a difference-in-differences model, exploiting the fact that local areas have different exposure to the lockdowns because of their employment composition. This approach has the advantage of allowing a causal interpretation of the results, under the identifying assumption of common trends.

The rest of this study is structured as follows. Section 2 describes the evolution of the pandemic in England and the policy responses. Section 3 presents the data. Section 4 discusses the empirical methodology. Section 5 presents the results, and Section 6 concludes.

2 Evolution of the pandemic and policy responses

The first confirmed case of Covid-19 in England was registered in York on January 30, 2020. By October 27, 2021, there had been $7,564,400$ positive tests and $139,056$ deaths with Covid-19 on the death certificate in England. By the same date, 86% of the adult population had received at least one dose of a Covid-19 vaccine and 79% had received two doses.[1]

Figure 1 shows the evolution of confirmed cases, mortality and vaccinations over time. The first wave of the pandemic peaked in April 2020 and is more visible in mortality data than in the number of confirmed cases. This is because tests were not routinely administered at that time and were only done for patients admitted to hospital. The second wave peaked in January 2021 and is visible both in the number of cases and in mortality. In June and July 2021 the number of confirmed cases increased rapidly again, but the increase in mortality was much smaller than in previous waves due to the success of the vaccination programme.

Figure 2 shows a time line of the policy responses to the pandemic. The first national lockdown

[1] Source: https://coronavirus.data.gov.uk

was announced on March 23, 2020. The government issued a stay-at-home order, with people not allowed to leave their home, except for essential medical needs, food shopping, exercise and work (for those who could not work from home). Several businesses were closed, including restaurants and pubs, sports venues, gyms, cinemas, hairdressers and all non-essential retail. All public gatherings were prohibited, except for members of the same household. Schools were closed for in-person teaching, except for children of keyworkers and children considered vulnerable. By June 2020, mortality numbers had decreased substantially and there was less pressure on the health care system. Restrictions were gradually eased, starting with the reopening of schools and then of non-essential retail, pubs and restaurants.

From September 2020, case numbers and deaths started increasing again. On October 14, 2020 the government announced a three-tier system of local restrictions in England. Local areas were classified into three alert levels: medium, high and very high. Areas with a very high alert level (Tier 3) faced stricter restrictions, but less strict than those imposed during the national lockdown. Schools did not close and non-essential retail remained open in most areas, but restaurants and pubs closed, except for takeaway and delivery services. Gatherings of up to six people were permitted, but only in public outdoor spaces.

Three weeks after the tier system was introduced, case numbers and deaths were still rising and the government responded by announcing a second national lockdown. This lockdown was in place for four weeks, until December 2, 2020. It imposed similar restrictions to the first national lockdown but this time schools did not close. Figure 1 suggests that this short lockdown was successful in turning the tide on infections and mortality, which declined during November. When the lockdown ended, the three-tier system of local restrictions came back into force. A new tier — Tier 4, "stay at home" — was introduced on December 19, 2020 in all London boroughs and other areas with high infection rates in response to a new variant of Covid-19, the Alpha variant. Tier 4 restrictions were effectively the same as those imposed during national lockdown.

December 2020 also marked the start of the Covid-19 vaccination programme in the UK. Vaccines were rolled out quickly in order of priority. The first six priority groups were residents and staff working in care homes for older adults (priority 1), those aged 80 or over and frontline health and social care workers (priority 2), those aged 75 or over (priority 3), those aged 70 or over and clinically extremely vulnerable individuals (priority 4), those aged 65 or over (priority 5), and adults aged 16 to 65 with certain medical conditions (priority 6). Vaccines were then offered to the rest of the population, by age group.

With the continuing rise in infections and mortality, the government imposed a third national lockdown on 6th January 2021. This lockdown introduced similar restrictions to the previous two national lockdowns. Schools were closed until March 8, 2021 and other lockdown restrictions were gradually eased from mid-April 2021. By this time, the vaccination rollout was proceeding at pace and more than half of the adult population in the UK had received a first dose of a Covid-19 vaccine. In June and July 2021, infection rates increased rapidly again, primarily due to the Delta variant. Because of widespread vaccination, the increase in infections was not accompanied by an increase in mortality and the government did not impose any restrictions on businesses or social gatherings.

3 Data

Data on the number of confirmed Covid-19 cases by MSOA and specimen date are taken from the UK government website, https://coronavirus.data.gov.uk/. These data measure the number of people with at least one positive Covid-19 test result, either lab-reported or from a rapid lateral flow test confirmed by a PCR test within 72 hours. These data are available at weekly frequency from March 19, 2020. Data on the number of deaths related to Covid-19 by MSOA are from the ONS and report the number of deaths with any mention of Covid-19 on the death certificate. Mortality data are available at monthly frequency and cover the period from March 2020 to April 2021.

I merge these data on infections and mortality with data on socioeconomic characteristics of MSOAs. Table 1 presents descriptive statistics and lists the data sources. Data on gender, ethnicity, age and household size are from the 2011 Census. Data on population and density are from the ONS 2019 population estimates. Data on annual household income are from the ONS 2018 income estimates for small areas. Data on the average number of National Health Service (NHS) outpatient appointments per person in 2019 were obtained by request from NHS Digital and are from the Hospital Episode Statistics. These health data reflect the general health of the local population, including the prevalence of comorbidities, better than self-reported measures of health available in the Census and in survey data.

Data on occupation by MSOA are from the 2011 Census and measure the number of usual residents aged 16 and over in employment by detailed (4 digit) occupation group. I then classify these occupations into those that can be done from home and those that cannot, and into those that require close physical proximity to others and those that do not.

To determine the feasibility of working from home, I use the classification in Dingel and Neiman (2020), which is based on responses to two surveys in the O*NET database — the work context questionnaire and the generalised work activities questionnaire. O*NET is a programme sponsored by the US Department of Labor and contains detailed information on the characteristics of different occupations. Broadly speaking, Dingel and Neiman classify an occupation as one that cannot be done from home if the occupation requires the worker to work outdoors every day or spend the majority of time walking or running, if the occupation exposes the worker to diseases, injuries or violent people or requires the use of protective equipment, if the occupation requires the use of machines, vehicles or equipment or requires working directly with the public. For physical proximity, I use the index from the O*NET work context questionnaire and split occupations into two groups using the median value of the index.

Using these two classifications, I then divide occupations into those that cannot be done from home and require close physical proximity to others — NHHP occupations — and those that do not meet one or both of these conditions. Table A1 in the Appendix lists the occupations in the NHHP group and further classifies them into occupations that were affected by closures during the national lockdowns and occupations that were allowed to remain open.

Figure 3 shows a map with the share of employment in NHHP occupations that were closed during lockdown in different MSOAs. Occupations closed during lockdown are primarily hospitality, entertainment and non-essential retail. Figure 3 shows that there is a large degree of variation across MSOAs in the share of employment in these occupations. This share is highest in urban areas — such as London, Leeds, Manchester, Liverpool, Sheffield and Nottingham — and in tourism areas — such as Cornwall and Bath. I use this cross-sectional variation in ex ante exposure to lockdowns to assess the impact of lockdowns on Covid-19 infection and mortality rates.

To explore the channel through which lockdowns may have a differential effect depending on the occupation composition of local areas, I use data from the Google Covid-19 community mobility report on time spent in different places — retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residences. The data show how numbers of visits and the length of stay at these different places changed compared with a baseline. The baseline is the median value for the corresponding day of the week during the five-week period from January 3 to February 6, 2020. The data come from users who have opted in to location history for their Google accounts. They are available at daily frequency, starting on February 15, 2020, and cover the whole UK and all local authority districts.

4 Empirical methodology

To examine the differential effects of national lockdowns by the occupation composition of local areas, I construct the share of employment in each MSOA in NHHP occupations that were closed during lockdown. Pubs, restaurants, gyms and non-essential shops were closed during lockdown. Retail businesses classified as essential remained open. Construction and manufacturing activities were also allowed to continue.

I estimate the following model:

$$\begin{aligned} Y_{m,i,t} &= \alpha ShareNHHPLockdown_m + \delta ShareNHHPLockdown_m \times Lockdown_t + \\ &\quad \lambda ShareNHHP_m + \beta X_m + \rho_t + \gamma_i + \epsilon_{m,i,t} \end{aligned} \tag{1}$$

The model is estimated using panel data, at weekly frequency for infections and monthly frequency for mortality. The dependent variable is either the number of Covid-19 cases per 100,000 people in week t or the number of Covid-19 deaths per 100,000 people in month t, for MSOA m in local authority i.

I estimate the model separately for each of the three national lockdowns. For infections, I focus on the second and third national lockdowns because data on infection rates at the start of the pandemic do not reflect the actual number of cases. At that stage of the pandemic, only patients admitted to hospital were tested for Covid-19. For mortality, I study the effect of all three national lockdowns. Each MSOA is weighted by its population and standard errors are clustered by MSOA to account for serial correlation.[2]

For infections, the model is estimated on weekly data. For the second lockdown, $Lockdown_t$ is equal to zero for the period from September 5 to November 4, 2020 and equal to one for the period from November 5 to December 1, 2020. For the third lockdown, $Lockdown_t$ is equal to zero for the period from December 2, 2020 to January 5, 2021 and equal to one for the period from January 6 to March 7, 2021. Mortality data are only available by MSOA at monthly frequency. For the first lockdown, $Lockdown_t$ is equal to zero for March 2020 and equal to one for April and May 2020. For the second lockdown, $Lockdown_t$ is equal to zero for September and October 2020 and equal to one for November 2020. For the third lockdown, $Lockdown_t$ is equal to zero for December 2020 and equal to one for January and February 2021.

The model can be interpreted as a difference-in-differences model, where the treatment is the lockdown and exposure to treatment is captured by the share of employment in NHHP occupations that were closed during lockdown ($ShareNHHPLockdown_m$).[3] MSOAs with a high value of this share may also differ in other important ways that independently influence Covid-19 infections and mortality. To address this concern, I first report the correlation between this ex ante exposure measure and a set of socioeconomic characteristics. Each row in Table 2 regresses the 2011 employment share in NHHP occupations that were closed during lockdown on one of these socioeconomic covariates. Occupations closed during lockdown are primarily hospitality, entertainment and non-essential retail. MSOAs with a larger share of employment in these occupations tend to be urban areas, with a younger population, a larger share of ethnic minority population, higher population density, a smaller average household size, higher household income and better health.

The results in Table 2 show that exposure to lockdown is not random. This could pose a challenge to my empirical methodology by introducing omitted variable bias. The direction of this bias is not a priori clear. For example, MSOAs with a younger population have lower Covid-19 mortality rates, but MSOAs with a larger share of ethnic minority population have higher Covid-19 mortality rates.[4] For infection rates, there is the additional challenge — discussed in Borjas (2020)

[2] Results without weighting and without clustering are substantially similar to the baseline results.

[3] Primary and secondary schools remained open during the second lockdown but were closed during the third lockdown. This difference is not captured by my exposure measure because school teachers are classified as occupations that can be done from home.

[4] The link between Covid-19 mortality and ethnicity is studied, for example, in Mathur et al. (2021) and ONS (2020).

— that infection rates depend on both the frequency of tests and the fraction of positive tests among those tested. These two dimensions are difficult to disentangle because data on the total number of tests by MSOA are not available. The frequency of testing is likely to depend on the socioeconomic characteristics of the local area. For example, low income individuals may be less likely to test for Covid-19 because they would need to take time off work if they tested positive. Borjas (2020) finds that this is true for New York City neighbourhoods.

I use three empirical strategies to mitigate concerns about omitted variable bias. First, I include the socioeconomic covariates in Table 2 as additional controls in the model (X_m). Second, I exploit the fine level of geographic disaggregation in the data and include local authority fixed effects (γ_i). These capture observable and non-observable characteristics of local authorities that have not been explicitly included in the model. Third, because I am estimating a difference-in-differences model, any differences in mortality rates, the frequency of testing or the share of positive tests across MSOAs with different levels of exposure to lockdown that do not change over time are differenced out.

The model also includes time fixed effects (ρ_t) and the share of employment in NHHP occupations ($ShareNHHP_m$). Time fixed effects capture factors that change over time but affect all local areas in a similar way, for example, seasonal variation in infections and mortality. By including the share of employment in NHHP occupations as a control, I am comparing MSOAs with the same share of employment in these occupations. However, in some of these MSOAs, these jobs are mostly in occupations closed during lockdown (such as pubs, restaurants and non-essential retail) whereas in other MSOAs, these jobs are mostly keyworkers in occupations that remained open (for example, health care, essential retail, construction and manufacturing).

The thought experiment is the following. Suppose there are only two MSOAs and both have 50% of employment in NHHP occupations. In one of these MSOAs all of this employment is in sectors closed during lockdown, whereas in the other MSOA all of this employment are keyworkers in sectors classified as essential and allowed to remain open during lockdown. I use the second MSOA to assess the counterfactual level of Covid-19 infections and mortality in the absence of the lockdown in the first MSOA.

The identification assumption — common trends — is that infections and mortality in these different MSOAs would have followed the same trend if the lockdown had not been imposed. As a first check of the validity of this identification assumption, I split MSOAs into quintiles based on the share of employment in NHHP occupations closed during lockdown ($ShareNHHPLockdown_m$). MSOAs more exposed to lockdown are in top quintile and MSOAs less exposed to lockdown are in bottom quintile. Figure 4 plots Covid-19 infections rates and mortality rates over time for high and low exposure MSOAs and the difference between the two groups.

During the first two weeks of October 2020, infection rates increased more rapidly in high exposure MSOAs. However, this trend reversed in the second half of October 2020, when infection rates increased more rapidly in low exposure MSOAs. This is probably because the tier system of local restrictions introduced on October 14, 2020 led to a reduction in the growth of infections in high exposure MSOAs. Even though the highest level of restrictions at that time (Tier 3) was less strict than during lockdowns, hotels, restaurants and pubs were already closed, except for takeaway and delivery. For the third lockdown, there was a noticeably steeper increase in infections in high exposure MSOAs prior to the lockdown, followed by a steeper reduction in infections during the lockdown. The difference in infection rates between high and low exposure MSOAs started to narrow about two weeks before the third lockdown, at the time of the introduction of the new Tier 4, which imposed restrictions as strict as those during national lockdown.

Covid-19 mortality followed identical trends in high and low exposure MSOAs before the first lockdown. The lockdown reduced mortality for both quintiles, but the reduction was steeper in high exposure MSOAs. The second lockdown did not reduce mortality for these two quintiles, but it reduced the rate of growth of mortality in high exposure MSOAs compared with low exposure MSOAs. The third lockdown reduced mortality in both quintiles. The reduction was initially larger in high exposure MSOAs, but the impact on the difference between high and low exposure MSOAs was smaller than during the first two national lockdowns.

To account for differences in pre-trends across high and low exposure MSOAs, I split MSOAs into percentiles of the distribution of the share of employment in NHHP occupations closed during lockdown ($ShareNHHPLockdown_m$). I extend the model to include a set of 100 linear trends, specific to each of these percentiles.

5 Results

5.1 Baseline results

Table 3 reports the results of estimating model (1) with and without MSOA percentile-specific trends.[5] The coefficient δ captures the differential effects of lockdowns on infections and mortality in local areas with a larger share of employment in NHHP occupations that were closed during lockdown, compared with local areas with a similar share of employment in NHHP occupations, but where more of those occupations are keyworkers that continued to work during lockdown.

Lockdowns have a negative and statistically significant effect on Covid-19 infection and mortality rates. The results are robust to the inclusion of MSOA percentile-specific trends. To interpret the results, I compare MSOAs at the top and bottom quintiles of the distribution of the share of employment in NHHP occupations closed during lockdown. The top quintile is 36% and the bottom quintile is 28%, a difference of 8 percentage points. I then multiply this difference by the regression coefficients in Table 3. I find that an increase in the share of employment in NHHP occupations closed during lockdown by 8 percentage points would have decreased weekly infections by 78 cases per 100,000 people during the second lockdown and 15 cases by 100,000 people per week during the third lockdown. Mortality would have decreased by 3 deaths per 100,000 people per month during the first and second lockdowns, but the effect on mortality for the third lockdown is not statistically significant. These are sizeable effects. Compared to a mean value of 119 weekly infections per 100,000 people and 15 monthly deaths per 100,000 people, the infection rate would have fallen by 66% and the mortality rate would have fallen by 20%.

5.2 Exploring the mechanism

To understand how national lockdowns may have a differential effect on Covid-19 infections and mortality depending on the occupation composition of local areas, I use Google mobility data to test whether more people stayed at home during lockdowns in local areas with a larger share of employment in occupations that were closed during lockdowns. These data are available for the UK as a whole and for all local authority districts.

[5] For the effect of the first lockdown on mortality, I do not include MSOA percentile-specific trends because there are not enough data pre-treatment at monthly frequency to estimate the trends precisely.

Figure 5 shows broad trends for the UK as a whole. As expected, the pandemic increased time spent at home and in parks and reduced time spent at retail and recreational places, transit stations and workplaces. Time spent shopping for groceries and in pharmacies also decreased, but less sharply than for other activities. The first lockdown had a larger effect on time spent in different places than the two subsequent lockdowns. There is evidence of a change in mobility patterns starting about two weeks before the third national lockdown, probably reflecting the introduction of Tier 4 restrictions in some local areas. During the summer of 2021, mobility patterns gradually moved closer to the baseline. By September 2021, time spent at home and shopping for groceries or in pharmacies was back to baseline levels, but time spent at retail and recreational places, transit stations and workplaces was still below baseline and time spent in parks was more than 50% above baseline.

To test whether national lockdowns reduce Covid-19 infections by allowing workers in occupations closed by lockdown to spend more time at home, I estimate a difference-in-differences model similar to model (1), but with the dependent variable being the change in time spent at home relative to the baseline ($Home_{i,t}$). Because Google mobility data are not available by MSOA, the model is estimated by local authority district, denoted by subscript i.

$$Home_{i,t} = \delta ShareNHHPLockdown_i \times Lockdown_t + \rho_t + \gamma_i + \epsilon_{i,t} \tag{2}$$

To remove the effect of weekends, I calculate 7-day averages and estimate the model using this new dataset at weekly frequency. The model includes time fixed effects and local authority fixed effects.

I estimate the model separately for all three national lockdowns. For the first lockdown, the indicator $Lockdown_t$ is set to zero for the period from February 20 to March 22, 2020, and set to one for the period from March 23 to May 31, 2020. The indicators for the second and third lockdowns are the same as in model (1). The occupation shares are calculated in the same way as for model (1), but by local authority district rather than MSOA. As before, each local authority is weighted by its population and standard errors are clustered by local authority to account for serial correlation.[6]

[6] Results are robust to weighting and clustering.

To check the validity of the common trends assumption, I adopt the same approach as for model (1) and estimate the model including linear trends specific to each percentile of the distribution of the share of employment in NHHP occupations closed during lockdown ($ShareNHHPLockdown_i$). This share is now calculated at the local authority level.

Figure 6 compares the evolution in the percentage change in time spent at home relative to baseline in high and low exposure local authorities. These are the top and bottom quintile local authorities based on the share of employment in NHHP occupations closed during lockdown. Time spend at home increased substantially with the first national lockdown. This increase was visibly larger in high exposure local authorities. The change in time spent at home then remained larger for high exposure local authorities than for low exposure local authorities. The difference between the two groups fluctuates over time. The second lockdown increased this difference by a small amount and the third lockdown led to a larger increase in the difference between the two groups of local authorities.

The estimation results, reported in Table 4, are consistent with these trends. There is evidence that all three national lockdowns increased time spent at home by more in local authority districts where more people work in sectors closed during lockdown. The first lockdown had the largest effect on time spent at home and the second lockdown had the smallest effect. To have a sense of the magnitude of these coefficients, I compare local authorities at the top and bottom quintiles of the share of employment in NHHP occupations closed during lockdown. The top quintile is 35% and the bottom quintile is 28%, a difference of 7 percentage points. I then multiply this difference by the regression coefficient in column (2) of Table 4 and find that, for the first lockdown, the percentage change in time spent at home relative to baseline was about 1.4 percentage points higher in local authorities in the top quintile compared with the bottom quintile. Compared to a mean value of 12, this corresponds to an increase of about 12% in the percentage change in time spent at home.

6 Conclusions

Many governments have responded to the Covid-19 pandemic by imposing national lockdowns. Lockdowns are a combination of policies, including stay-at-home orders, restrictions on social gatherings and business closures. Their effects on health and economic outcomes are still not fully understood. In this study, I evaluate the effects of national lockdowns on Covid-19 infection rates and mortality rates using evidence from the three national lockdowns introduced in England in 2020 and early 2021.

The novelty of my analysis lies in part in using data for small local areas (MSOAs). This allows me to include local authority fixed effects in the regressions and reduce selection bias. I am also able to construct a quasi-experiment to study the effects of national lockdowns by exploiting variation across local areas in ex ante exposure to lockdown, as measured by the share of employment in occupations that cannot be done from home, require close physical proximity to others, and were closed during lockdown — for example, restaurants and non-essential retail.

My results show that national lockdowns reduced infections and mortality by more in local areas that have a larger share of employment in sectors closed during lockdown. These effects are larger for the first national lockdown that started in March 2020 and seem to be partly due to an increase in time spent at home in these local areas as a result of lockdown.

These results are useful to inform our understanding of how national lockdowns affect Covid-19 infections and mortality. The methodology used in this paper of exploiting variation in exposure to lockdowns across local areas at a micro-level could be useful to analyse the effect of lockdowns on non-health outcomes, for example income and employment.

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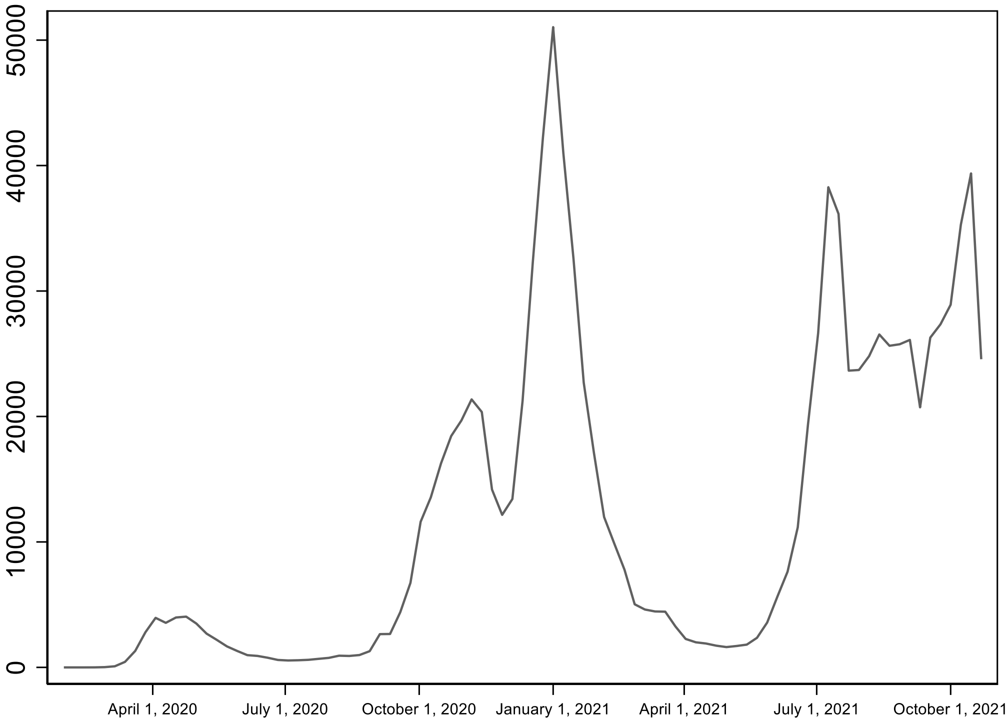
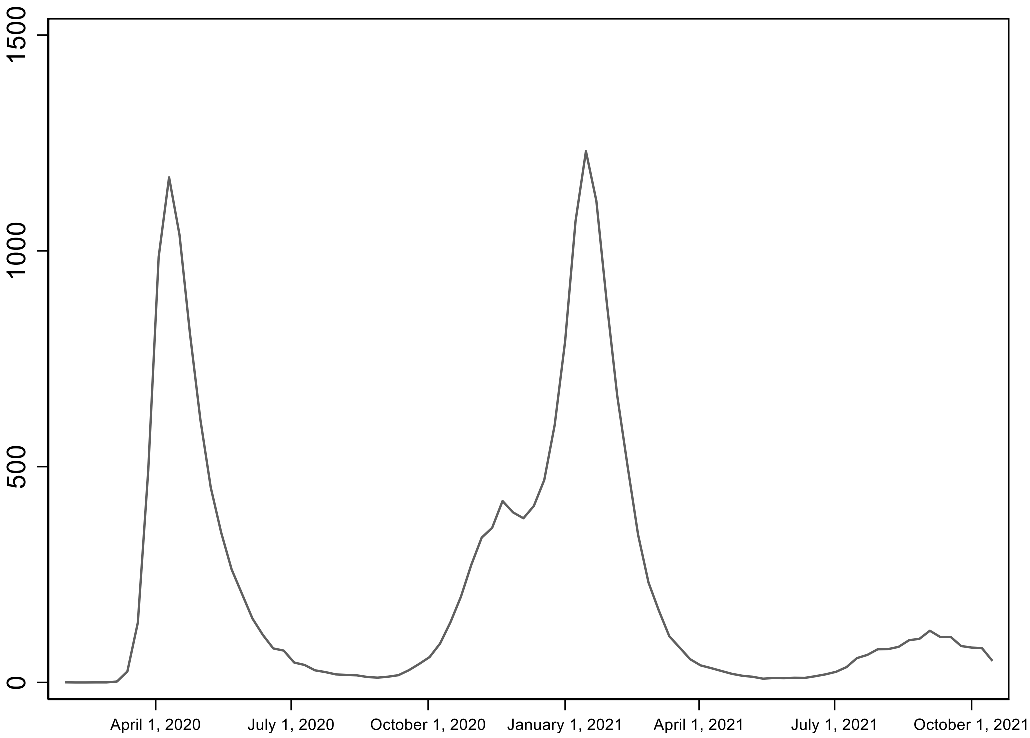
Figure 1: Cases, mortality and vaccinations over time

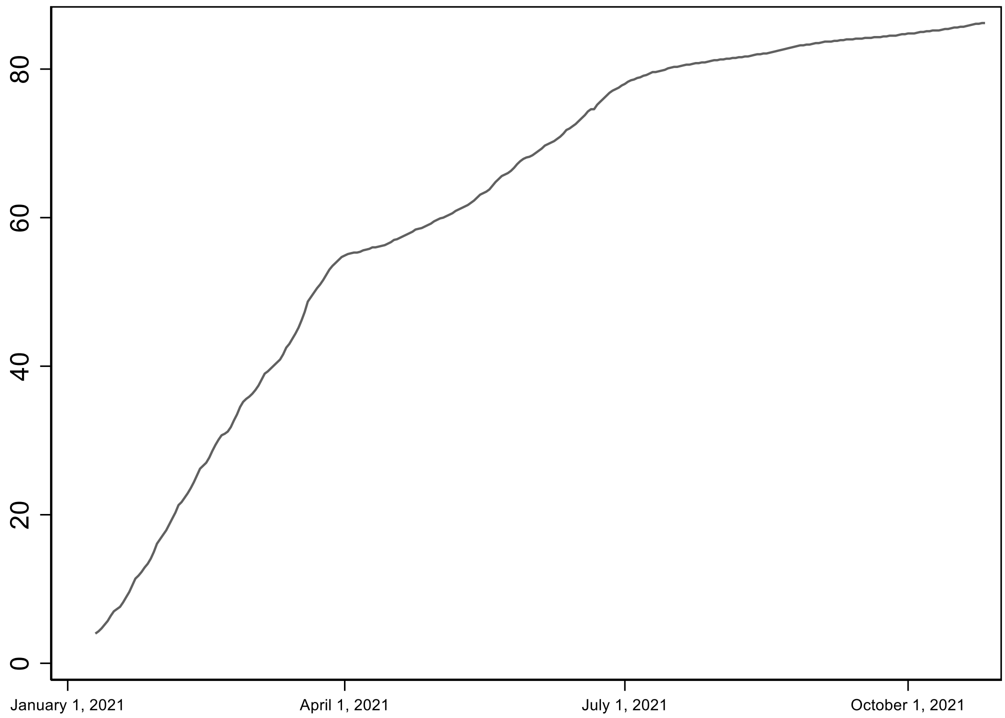
A. New daily covid-19 cases (7-day average)



B. New daily covid-19 deaths (7-day average)



C. Vaccination uptake – first dose (cumulative, %)



Notes: Cases measure the number of people with at least one positive Covid-19 test result, by specimen date. Deaths measure the number of daily deaths with Covid-19 on the death certificate, by date of death. Vaccination uptake is the percentage of people aged 18 and over who have received a Covid-19 vaccination, by date reported. Source: https://coronavirus.data.gov.uk

Figure 2: Timeline of policy responses to the pandemic in England

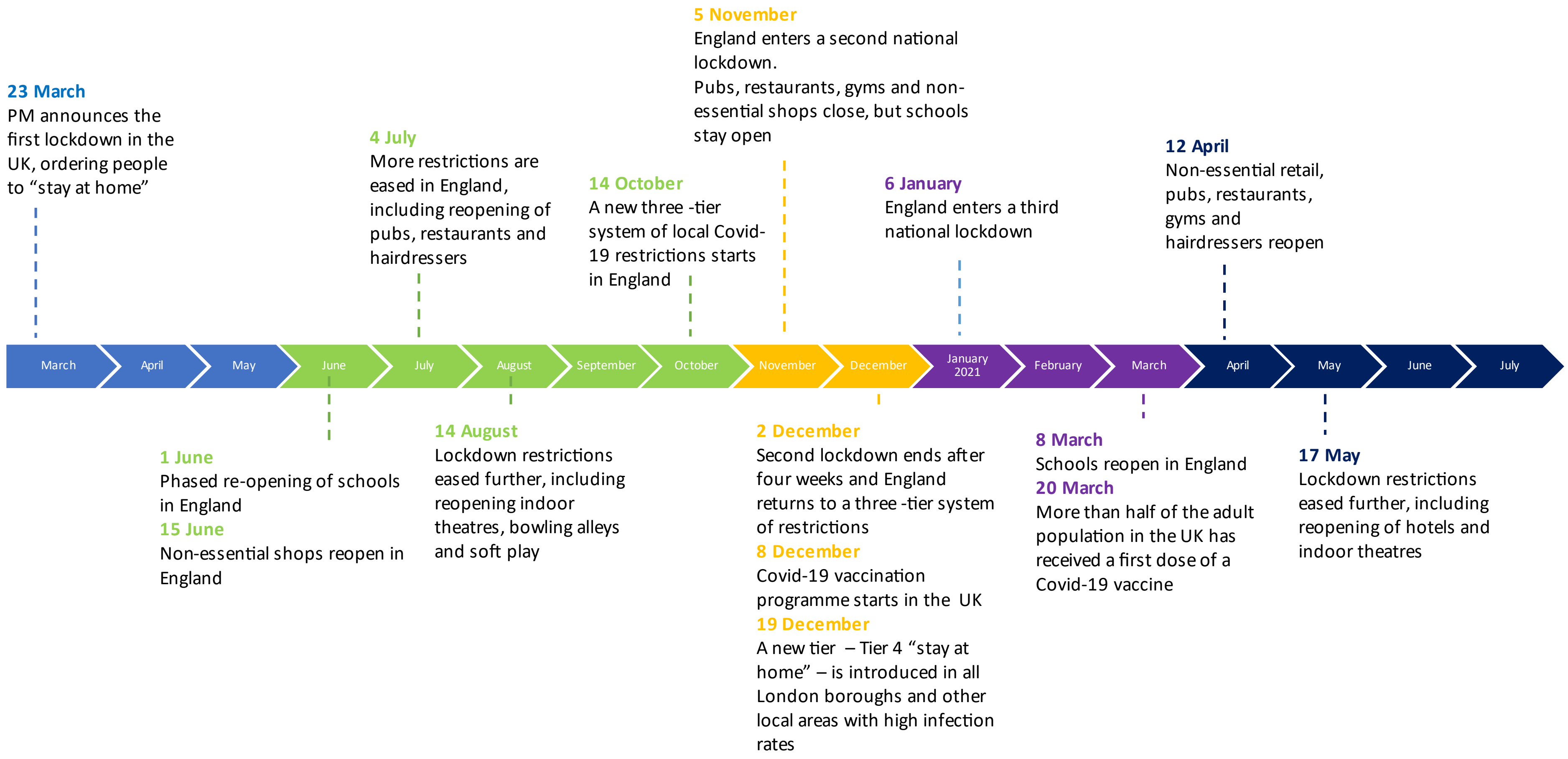


Table 1: Descriptive statistics and data sources

	Mean	Standard deviation	Source
Weekly panel			
Covid-19 cases per 100,000 people	119.129	196.969	https://coronavirus.data.gov.uk/ (reported weekly from March 19, 2020); population from ONS 2019 population estimates.
Percentage change in time spent at home relative to baseline	12.440	6.799	Google Covid-19 community mobility report, UK (reported daily from February 15, 2020); 7-day average of daily data. The baseline is the median value, for the corresponding day of the week, during the five-week period from January 3 to February 6, 2020.
Monthly panel			
Covid-19 deaths per 100,000 people	15.019	27.494	ONS (reported monthly from March 2020 to April 2021); population from ONS 2019 population estimates.
MSOA-level data – cross-section of 6,789 MSOAs			
Percent female	50.667	1.687	2011 Census
Percent age 60 and over	24.691	8.241	2011 Census
Percent black/African/Caribbean/black British	3.261	6.322	2011 Census
Percent Asian/Asian British	7.249	12.056	2011 Census
Log population density	2.819	1.519	ONS 2019 population estimates
Log average household size	0.859	0.094	2011 Census
Log total annual household income	10.665	0.219	ONS 2018 income estimates for small areas
Average number of NHS outpatient appointments per person	2.203	0.518	NHS Digital Hospital Episode Statistics (HES), outpatient appointments by patient MSOA for the period January 2019 - December 2019; population from ONS 2019 population estimates
Percent employment in NHHP occupations	43.119	8.221	Classification into occupations that can be done from home and those that cannot from Dingel and Neiman (2020). Classification into high and low proximity from O*NET, work context, physical proximity index (split by the median of the index). Number of usual residents aged 16 and over in employment by occupation (full detail, 4 digits) from Census 2011.
Percent employment in NHHP occupations closed during lockdown	32.248	6.207	Classification of occupations into closed or open during lockdown is from The Health Protection (Coronavirus, Restrictions) (England) Regulations 2020 No. 350, available at https://www.legislation.gov.uk/uksi/2020/350/made.

Figure 3: Share of employment in NHHP occupations closed during lockdown

The figure shades MSOAs by the share of employment in 2011 in NHHP occupations that were closed during lockdown. MSOAs with a darker shading have a larger share of employment in NHHP occupations that were closed during lockdown. These occupations are listed in Table A1 in the Appendix.

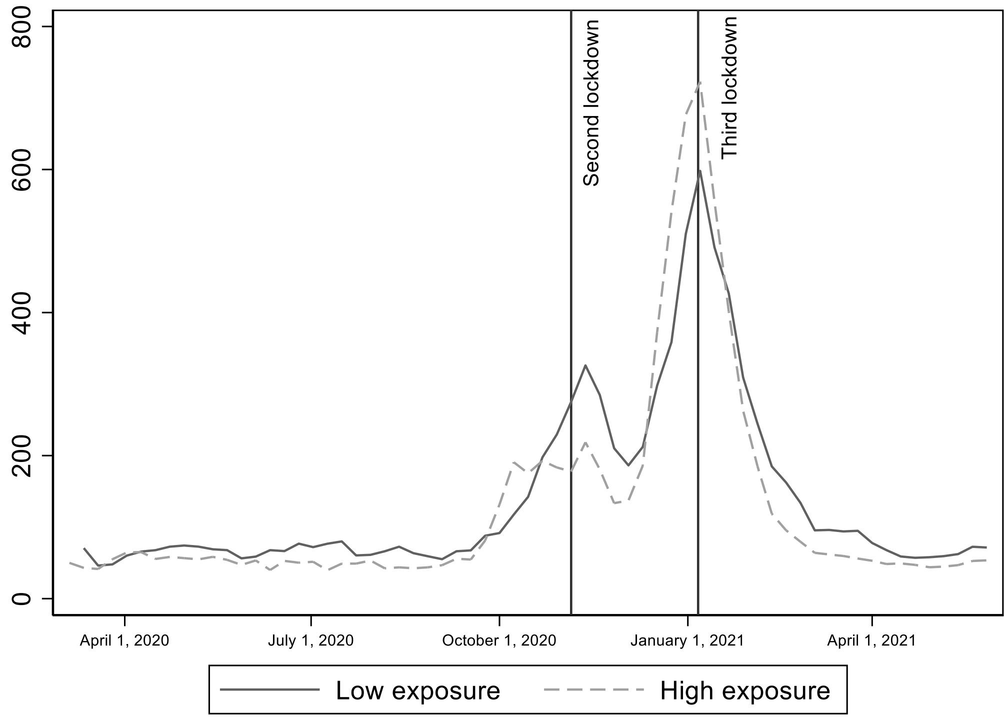
Table 2: Correlation of the 2011 share of employment in NHHP occupations closed during lockdown with other socioeconomic characteristics at MSOA level

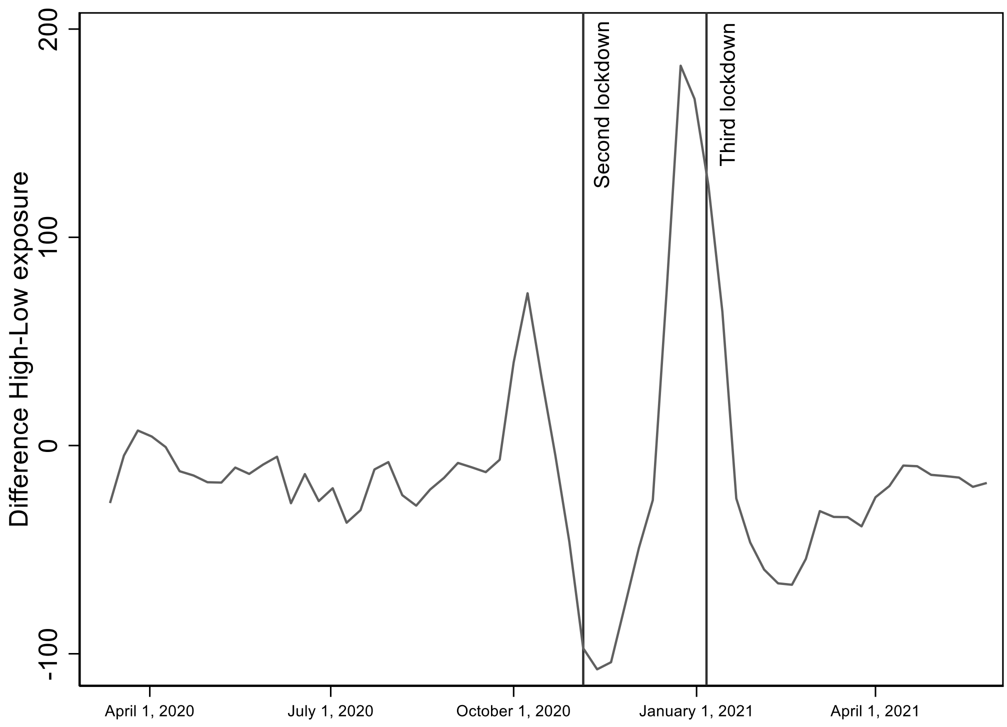
	Coefficient	R^2
Percent female	-0.769***	0.044
	(0.008)	
Percent age 60 and over	-0.222***	0.087
	(0.012)	
Percent Black/African/Caribbean/Black British	0.310***	0.100
	(0.014)	
Percent Asian/Asian British	0.120***	0.055
	(0.008)	
Log population density	1.174***	0.083
	(0.055)	
Log average household size	-5.619***	0.007
	(1.198)	
Log total annual household income	5.622***	0.039
	(0.373)	
Average number of NHS outpatient appointments per person	-0.607***	0.003
	(0.195)	

Notes: Each row reports results of a univariate regression of the share of employment in NHHP occupation closed during lockdown on different observable variables and a constant. Number of observations: 6,789 MSOAs. Robust standard errors in parentheses. *** Significant at the 1% level; ** significant at the 5% level; *significant at the 10% level.

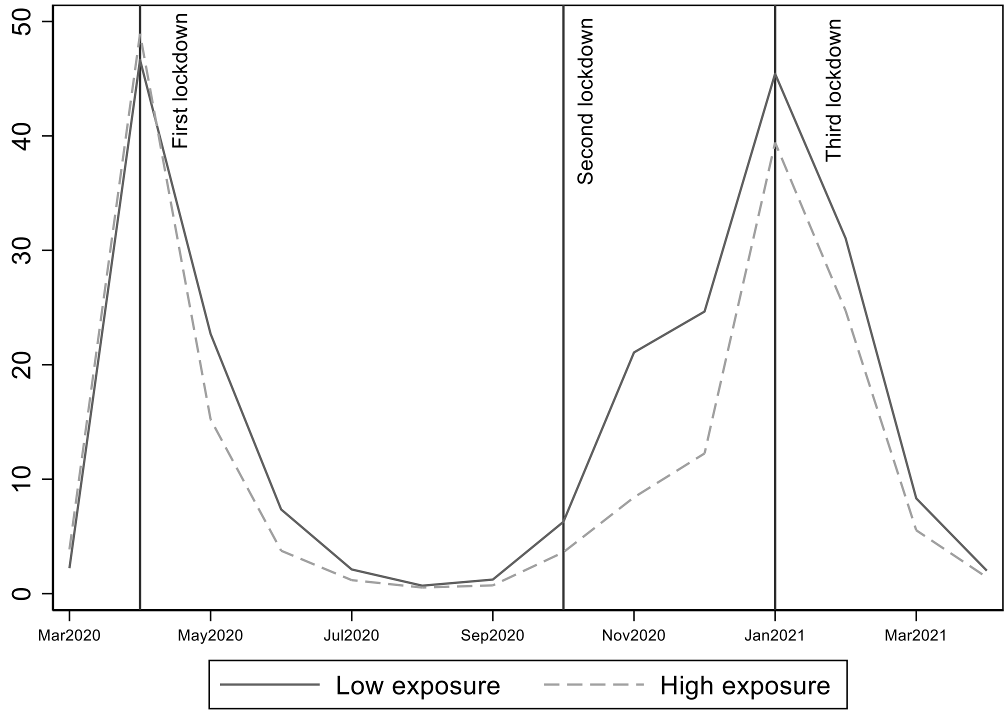
Figure 4: Infection rates and mortality rates for High and Low exposure MSOAs

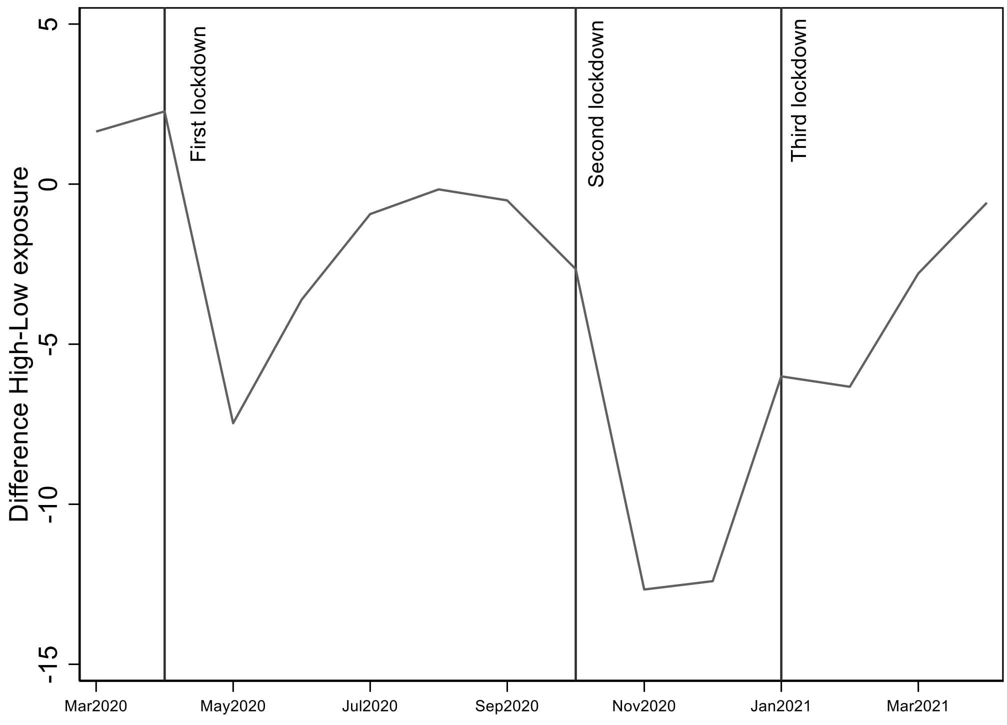
A. Covid-19 cases per 100,000 people





B. Covid-19 deaths per 100,000 people





Notes: High and low exposure MSOAs are the top and bottom quintile MSOAs based on the share of employment in NHHP occupations closed during lockdown. The top panels show Covid-19 infection rates and mortality rates. The bottom panels show the difference in infection rates and mortality rates between high and low exposure MSOAs.

Table 3: Differential effect of national lockdowns on Covid-19 infections and mortality by occupation composition

A. Covid-19 cases per 100,000 people

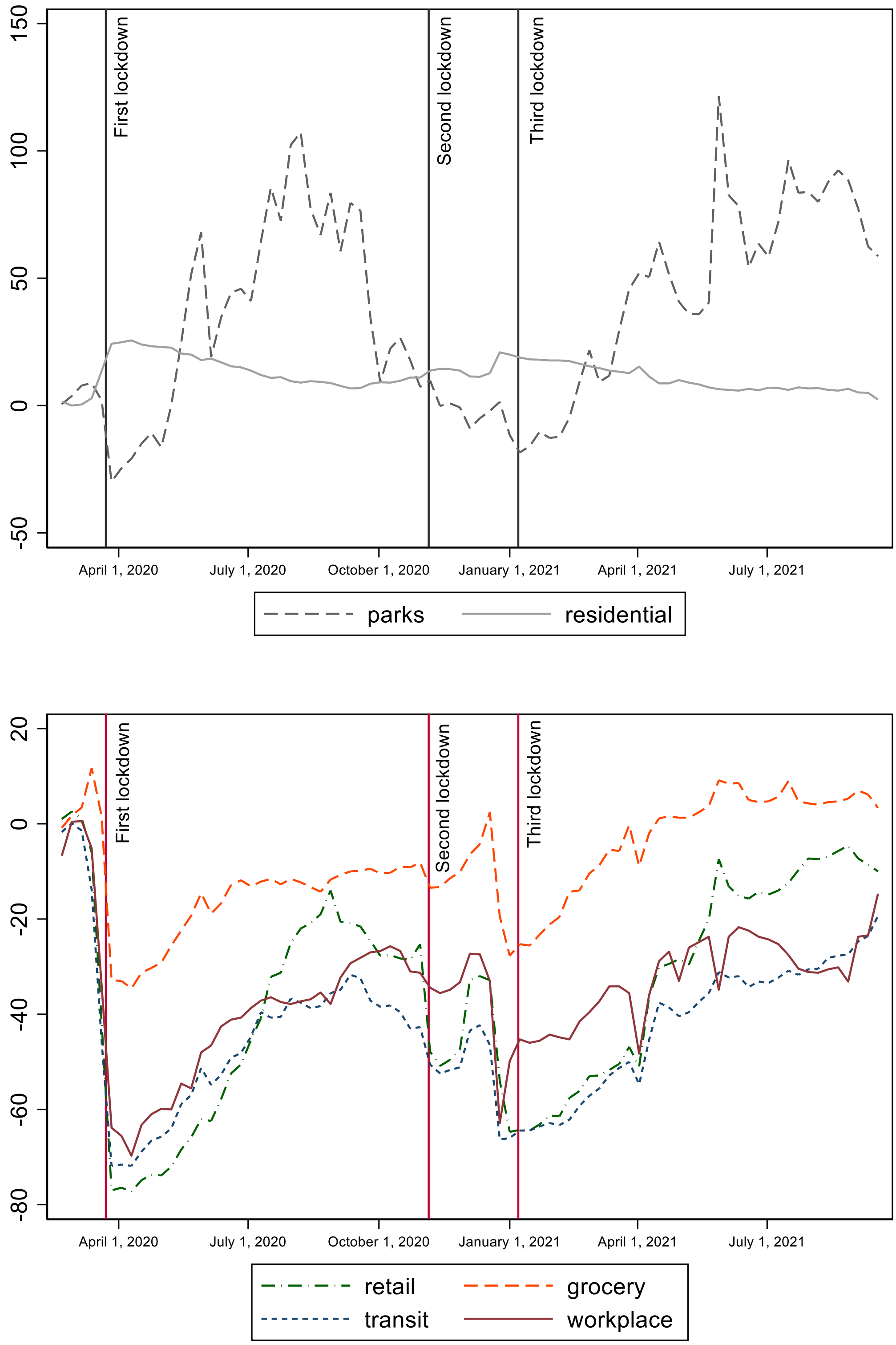
	(1)	(2)	(3)	(4)
Share of NHHP occupations closed by lockdown × Second lockdown	-8.238*** (0.687)	-9.740*** (1.245)		
Share of NHHP occupations closed by lockdown × Third lockdown			-3.718*** (0.361)	-1.907*** (0.427)
MSOA percentile-specific trends	No	Yes	No	Yes
Observations	81,468	81,468	95,046	95,046
R^2	0.465	0.478	0.597	0.600

B. Covid-19 deaths per 100,000 people

	(1)	(2)	(3)	(4)	(5)
Share of NHHP occupations closed by lockdown × First lockdown	-0.410*** (0.048)				
Share of NHHP occupations closed by lockdown × Second lockdown		-0.557*** (0.033)	-0.347*** (0.041)		
Share of NHHP occupations closed by lockdown × Third lockdown				0.179*** (0.055)	0.103 (0.116)
MSOA percentile-specific trends	No	No	Yes	No	Yes
Observations	20,367	20,367	20,367	20,367	20,367
R^2	0.378	0.311	0.323	0.2653	0.273

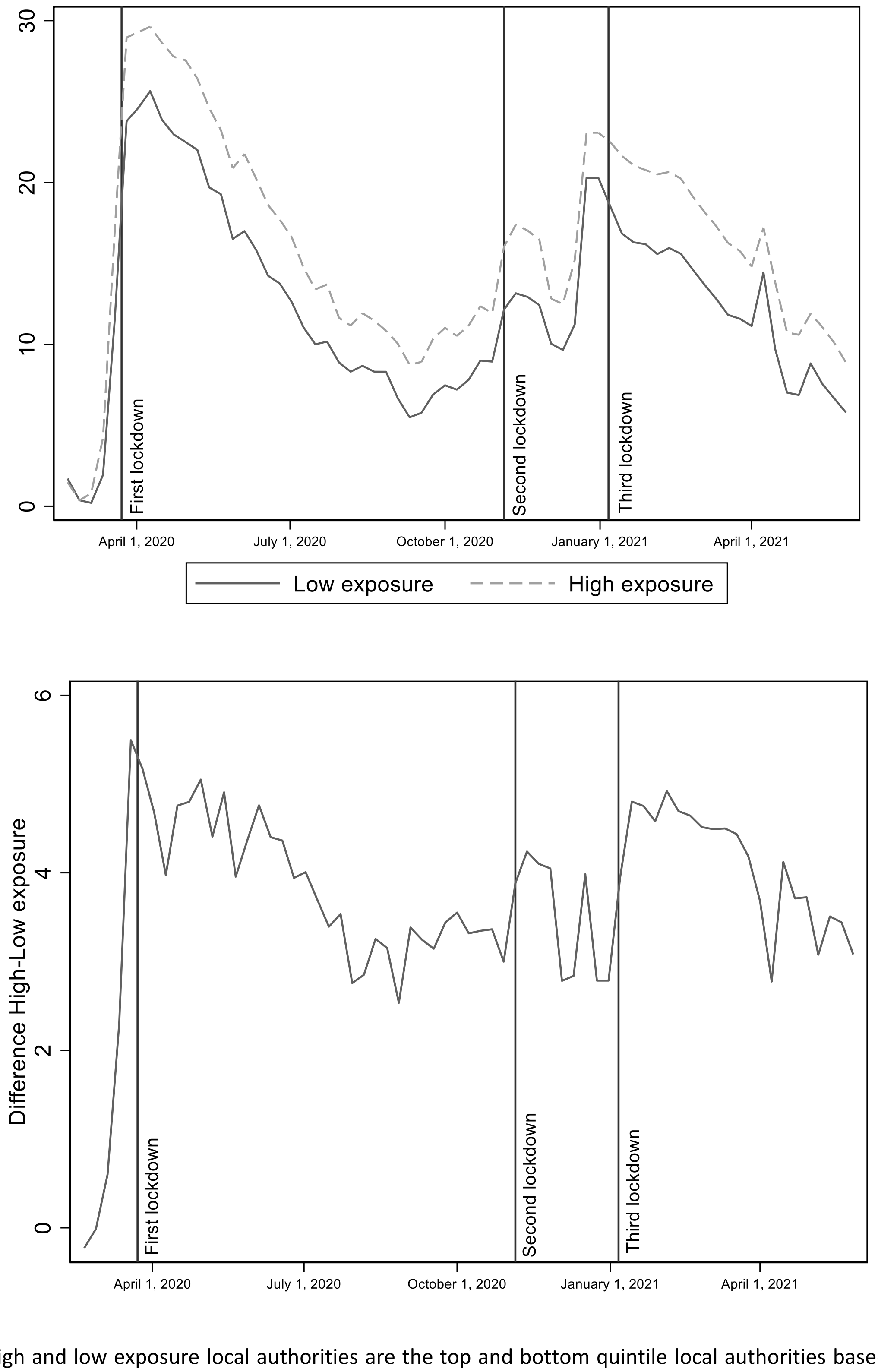
Notes: Weighted OLS by population size. Standard errors clustered by MSOA in parentheses. MSOA percentile-specific trends are linear time trends specific to each percentile of the share of employees in NHHP occupations who work in businesses closed during lockdown. Regressions include local authority and time fixed effects and control for the share of employment in NHHP occupations, the share of employment in NHHP occupation closed during lockdown, percent female, percent age 60 and over, percent Black/African/Caribbean/Black British, percent Asian/Asian British, log population density, log average household size, log total annual household income and average number of NHS outpatient appointments per person. *** Significant at the 1% level; ** significant at the 5% level; *significant at the 10% level.

Figure 5: Mobility trends in the UK



Notes: Percentage change (7-day average) in time spent at different categories of places compared with the median value, for the corresponding day of the week, during the five-week period January 3 to February 6, 2020.

Figure 6: Percentage change in time spent at home relative to baseline for High and Low exposure MSOAs



Notes: High and low exposure local authorities are the top and bottom quintile local authorities based on the share of employment in NHHP occupations closed during lockdown. The top panel shows the percentage change (7-day average) in time spent at home compared with the median value, for the corresponding day of the week, during the five-week period January 3 to February 6, 2020. The bottom panels show the difference in the percentage change in time spent at home between high and low exposure local authorities.

Table 4: Differential effects of national lockdowns on time spent at home by occupation composition

	(1)	(2)	(3)	(4)	(5)	(6)
Share of NHHP occupations closed by lockdown × First lockdown	0.264***	0.204***				
	(0.024)	(0.031)				
Share of NHHP occupations closed by lockdown × Second lockdown			0.068***	0.061***		
			(0.011)	(0.015)		
Share of NHHP occupations closed by lockdown × Third lockdown					0.125***	0.116***
					(0.010)	(0.011)
Local authority percentile-specific trends	No	Yes	No	Yes	No	Yes
Observations	4,632	4,632	3,774	3,774	4,397	4,397
R^2	0.984	0.986	0.977	0.979	0.968	0.970

Notes: The dependent variable is the percentage change in time spent at home relative to the baseline. Weighted OLS by population size. Standard errors clustered by local authority district in parentheses. Local authority percentile-specific trends are linear time trends specific to each percentile of the share of employees in NHHP occupations who work in businesses closed during lockdown. Regressions include local authority and time fixed effects. *** Significant at the 1% level; ** significant at the 5% level; *significant at the 10% level.

APPENDIX

Table A1: List of NHHP occupations and classification into those closed during national lockdown and those allowed to remain open

Occupation	Lockdown
1170 Senior Officers in Protective Services	0
1223 Restaurant and catering establishment managers and proprietors	1
1224 Publicans and managers of licensed premises	1
1225 Leisure and sports managers	1
1253 Hairdressing and beauty salon managers and proprietors	1
1254 Shopkeepers and proprietors: wholesale and retail	1
2122 Mechanical engineers	0
2211 Medical practitioners	0
2212 Psychologists	0
2213 Pharmacists	0
2214 Ophthalmic opticians	0
2215 Dental practitioners	0
2216 Veterinarians	0
2217 Medical radiographers	0
2218 Podiatrists	0
2219 Health professionals n.e.c.	0
2221 Physiotherapists	0
2222 Occupational therapists	0
2223 Speech and language therapists	0
2229 Therapy professionals n.e.c.	0
2231 Nurses	0
2232 Midwives	0
2436 Construction project managers and related professionals	0
2443 Probation officers	0
2471 Journalists, newspaper and periodical editors	0
3111 Laboratory technicians	0
3112 Electrical and electronics technicians	0
3113 Engineering technicians	0
3116 Planning, process and production technicians	0
3213 Paramedics	0
3216 Dispensing opticians	0
3217 Pharmaceutical technicians	0
3218 Medical and dental technicians	0
3219 Health associate professionals n.e.c.	0
3310 Protective Service Occupations	0
3413 Actors, entertainers and presenters	1
3414 Dancers and choreographers	1
3415 Musicians	1
3511 Air traffic controllers	0
3512 Aircraft pilots and flight engineers	0
3513 Ship and hovercraft officers	0

3546 Conference and exhibition managers and organisers	1
4123 Bank and post office clerks	0
4133 Stock control clerks and assistants	0
4134 Transport and distribution clerks and assistants	0
4135 Library clerks and assistants	1
5213 Sheet metal workers	0
5214 Metal plate workers, and riveters	0
5216 Pipe fitters	0
5221 Metal machining setters and setter-operators	0
5223 Metal working production and maintenance fitters	0
5225 Air-conditioning and refrigeration engineers	0
5231 Vehicle technicians, mechanics and electricians	0
5232 Vehicle body builders and repairers	0
5234 Vehicle paint technicians	0
5235 Aircraft maintenance and related trades	0
5236 Boat and ship builders and repairers	0
5237 Rail and rolling stock builders and repairers	0
5241 Electricians and electrical fitters	0
5311 Steel erectors	0
5312 Bricklayers and masons	0
5313 Roofers, roof tilers and slaters	0
5314 Plumbers and heating and ventilating engineers	0
5315 Carpenters and joiners	0
5316 Glaziers, window fabricators and fitters	0
5319 Construction and building trades n.e.c.	0
5321 Plasterers	0
5322 Floorers and wall tilers	0
5412 Upholsterers	0
5414 Tailors and dressmakers	0
5431 Butchers	0
5433 Fishmongers and poultry dressers	0
5434 Chefs	1
5435 Cooks	1
5436 Catering and bar managers	1
5441 Glass and ceramics makers, decorators and finishers	0
5443 Florists	1
6131 Veterinary nurses	0
6141 Nursing auxiliaries and assistants	0
6142 Ambulance staff (excluding paramedics)	0
6143 Dental nurses	0
6144 Houseparents and residential wardens	0
6145 Care workers and home carers	0
6146 Senior care workers	0
6147 Care escorts	0
6148 Undertakers, mortuary and crematorium assistants	0
6211 Sports and leisure assistants	1

6214 Air travel assistants	1
6215 Rail travel assistants	1
6221 Hairdressers and barbers	1
6222 Beauticians and related occupations	1
7111 Sales and retail assistants	1
7112 Retail cashiers and check-out operators	1
7114 Pharmacy and other dispensing assistants	0
7115 Vehicle and parts salespersons and advisers	1
7123 Roundspersons and van salespersons	1
7124 Market and street traders and assistants	0
7125 Merchandisers and window dressers	1
8111 Food, drink and tobacco process operatives	0
8112 Glass and ceramics process operatives	0
8114 Chemical and related process operatives	0
8115 Rubber process operatives	0
8116 Plastics process operatives	0
8117 Metal making and treating process operatives	0
8118 Electroplaters	0
8121 Paper and wood machine operatives	0
8125 Metal working machine operatives	0
8131 Assemblers (electrical and electronic products)	0
8132 Assemblers (vehicles and metal goods)	0
8134 Weighers, graders and sorters	0
8135 Tyre, exhaust and windscreen fitters	0
8137 Sewing machinists	0
8139 Assemblers and routine operatives n.e.c.	0
8141 Scaffolders, stagers and riggers	0
8142 Road construction operatives	0
8143 Rail construction and maintenance operatives	0
8149 Construction operatives n.e.c.	0
8212 Van drivers	0
8213 Bus and coach drivers	0
8214 Taxi and cab drivers and chauffeurs	0
8215 Driving instructors	1
8231 Train and tram drivers	0
8232 Marine and waterways transport operatives	0
8233 Air transport operatives	0
8234 Rail transport operatives	0
8239 Other drivers and transport operatives n.e.c.	0
9120 Elementary construction occupations	0
9134 Packers, bottlers, canners and fillers	0
9211 Postal workers, mail sorters, messengers and couriers	0
9241 Security guards and related occupations	0
9242 Parking and civil enforcement occupations	0
9244 School midday and crossing patrol occupations	0
9249 Elementary security occupations n.e.c.	0

9251 Shelf fillers	0
9259 Elementary sales occupations n.e.c.	0
9260 Elementary storage occupations	0
9271 Hospital porters	0
9272 Kitchen and catering assistants	1
9273 Waiters and waitresses	1
9274 Bar staff	1
9275 Leisure and theme park attendants	1
9279 Other elementary services occupations n.e.c.	0

Notes: Classification of occupations by feasibility of working from home is from Dingel and Neiman (2020) and is based on the O*NET database. Classification of occupations by degree of physical proximity is from the index in the O*NET work context questionnaire. Classification of occupations into closed or open during lockdown is from The Health Protection (Coronavirus, Restrictions) (England) Regulations 2020 No. 350, available at https://www.legislation.gov.uk/uksi/2020/350/made.