Place-based pathologies: economic complexity drives COVID-19 outcomes in UK local authorities

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Abstract

COVID-19 outcomes differ according to socio-economic indicators. In this study, we find there is a specific structure to the differences among UK local authorities, as localities with a lower economic complexity index (ECI) registered significantly higher COVID-19 cases and deaths. We show that the ECI is a predictor of people's movements, with mobility declining in high ECI localities during the pandemic, but not in low ECI places where a higher proportion of people have high-risk jobs more likely to lead to virus transmission. Local economic structures shape people's pandemic experiences and this calls for strategies to reduce spatial inequalities.

Keywords: COVID-19, Economic complexity, Place, Mortality, Morbidity, Mobility

Introduction

It is clear that there are links between socio-economic factors and COVID-19 outcomes, but attention has largely focused on different individual characteristics. Our contribution in this paper is to show that the structure of the socio-economic environment in which individuals live and work, specifically as measured and described by economic complexity, is significantly associated with COVID-19 outcomes. A decrease in a local authority's economic complexity index (ECI) of one standard deviation is associated with an increase of approximately 656 more COVID-19 cases and 11 more deaths per 100,000 people. A summary measure of economic structure, ECI predicts the proportion of people in a locality working in high-risk jobs and the extent to which people continued to travel during the pandemic, rather than reducing their mobility. People living in a low ECI area had a higher chance of working in a high-risk job and continued to travel as much as they did previously to go to work. The implication of our finding is that addressing the unequal social incidence of the disease - and any future pandemics - cannot be addressed by tackling individual characteristics or risk factors separately. The challenge is a systemic one, with health outcomes intrinsically linked to the places people live and their socio-economic structures.

It was clear from the early days of the COVID-19 pandemic that its incidence was unequal (Saban et al., 2021, Valdano et al., 2021, Upshaw et al., 2021). Investigating the morbidity and mortality figures has revealed that socio-economic status (SES) is a matter of life and death when it comes to the way people are affected by the virus (Mena et al., 2021, Williamson et al., 2020, Neelon et al., 2020, Upshaw et al., 2021). For instance, communities with low SES have been infection hotspots (Mena et al., 2021), while people in low-skilled occupations (Mutambudzi et al., 2021) or members of ethnic minority groups (Patel et al., 2020) have suffered disproportionately in terms of COVID-19 mortality rates and morbidities. People's response to lockdown regulations (e.g. "stay home and save lives" messaging) has also been shown to vary according to socioeconomic status; people of lower socioeconomic status paid less heed as staying home was not a viable option given their employment, or their living accommodation limited options to self-isolate (Chang et al., 2021, Castro et al., 2021, Burström and Tao, 2020, Paremoer et al., 2021). This SES-hued profile exactly matched the profile of health conditions that are identified as COVID-19 risk factors, e.g. obesity, diabetes, smoking, etc. (Williamson et al., 2020); they too are disproportionately concentrated among people of low socio-economic status (Saban et al., 2021, Marmot, 2020). Testing rates are also influenced by SES, displaying the same social gradient (Mena et al., 2021). In fact, COVID-19 soon laid bare a socio-economic structure that was already contributing at scale to ill health and death (Upshaw et al., 2021, Marmot, 2020).

Measures of economic complexity provide a novel lens on the structure and distribution of economic activities across places, and have previously been shown to be strong predictors of both economic and health outcomes, e.g. income level and inequalities, social capital level, economic growth, and infant and child mortality rates (Hidalgo, 2021, Vu, 2020). Unlike traditional aggregate approaches to economic outcomes, for example, linking outputs such as Gross Domestic Product (GDP) with labour and capital inputs, the economic complexity approach draws on fine-grained data about economic activities in a location, such as exports, employment in different industries, or patents in different technology sectors, to infer information about the underlying productive capabilities. While such data is high-dimensional (e.g hundreds of countries exporting thousands of differentiated products), the economic complexity metrics provide a useful way of summarising this information into rankings of locations that concisely capture the similarities in their productive capabilities (Hidalgo, 2021, Cristelli et al., 2013), Author et al, 2019). At the country level, countries ranking high on the ECI tend to export more technologically sophisticated products, such as machinery and chemicals, while countries with low rankings are more likely to export products requiring less technologically sophisticated capabilities such as agricultural products or raw minerals (Bahar et al., 2014). Similar findings have been documented within countries. For example, within the United Kingdom Author et al. (2021) used data on local authority employment in different industries and showed that UK local authorities with high ECI tend to be specialised in knowledge-oriented industries such as finance, information and communication, and professional, science and technical activities, while local authorities with lower ECI rankings tend to be specialised in agriculture, manufacturing and mining activities (Author et al, 2021).

Despite the growing use of economic complexity concepts and metrics in several disciplines, public health studies have to date not applied them, even though the effects of community-level socio-economic status on health have always been acknowledged as an important factor (Marmot, 2020). In the two studies published so far (Innocenti et al., 2021, Vu, 2020), researchers have shown that complexity of economic structure at country and regional levels is a strong predictor of differences in fertility rates, life-expectancies, and neonatal, infant, and under-5 mortalities. Vu (2020) offered four hypotheses to explain the strong predictive power of economic complexity. First, higher complexity leads to enhanced capacity to create additional occupational choices, learning opportunities, higher incomes, and finally better healthcare funding, structure, and choices. Second, higher economic complexity is linked to more inclusive social institutions and lower income inequalities. Third, it is postulated that economies that rank high in complexity are more resilient to external shocks, improving population health outcomes when shocks occur. Fourth, there is a correlation between the complexity of economies and high quality human capital and capabilities and it is postulated that this relates to the positive link between better population health outcomes and productivity, as the latter translates to higher quality healthcare.

In the present study we investigate how economic complexity at local levels in the UK is associated with COVID-19 morbidities and mortalities. Our hypothesis was that the COVID-19 profile at local levels in the UK would be shaped by the complexity of economic systems in these localities and further that the characteristics of jobs and the associated mobility patterns are the channels through which this structural influence would operate. Human contact is the most important factor in terms of the risk of transmission and where contact increases, including for non-optional activities such as occupation, the number of cases and deaths will likely increase.

Our finding that the structure of a locality as summarised in the ECI is a strong predictor of COVID-19 outcomes is relevant to the UK government's levelling up ambitions, and more broadly to the need to integrate public health and economic policies.

Methods

To examine the link between economic complexity and COVID-19 morbidity and mortality rates, we began by estimating the following specification:

$$CM_i = \alpha + \beta ECI_{i.pre-covid} + \gamma X_{i.pre-covid} + \delta_j + \varepsilon_i \qquad (1)$$

where CM_i stands for COVID-19 mortality (morbidity) rate in region i. In our benchmark case, CM_i corresponds to the number of COVID-19 cases in each region. EC_i is the economic complexity index which is the main regressor of our analysis. X_i denotes a set of control variables that are likely to impact the COVID-19 morbidity and mortality rates across the UK localities. δ_j represents controls for time-invariant regional characteristics that can cloud the relationship between local economic complexity and COVID-19 outcomes. See Appendix A for definition of the variables.

Applying Ordinary Least Squares (OLS) to estimate equation (1) allowed us to obtain an estimate of partial correlation between ECI and COVID-19 morbidity and mortality rates captured by β. However, it is likely that the estimated OLS coefficient suffers from bias and correlation of regression errors. The bias is related to the possibility that relevant confounding variables are omitted from the benchmark model. It should be noted that the source of the bias in our model is unlikely to be related to any reverse causality between ECI and COVID-19 morbidity and mortality rates because there is unlikely to be a direct channel of influence running from morbidity and mortality rates to the locality's economic and productive structure. In fact, the ECI measure in our study is a lagged value, i.e. it relates to the pre-COVID-19 period, which obviates the possibility of such endogeneity.

To address the potential omitted variables bias, we first incorporated a set of key determinant factors shown by the existing literature to have significant effects on COVID-19 morbidity and mortality rates (Williamson et al., 2020, Upshaw et al., 2021, Zheng et al., 2020, Sze et al., 2020, Emami et al., 2020). To be precise, we examined the impact of deprivation status, measured by the index of multiple deprivation (IMD)-income average, as a proxy for community socioeconomic status, which is known to have a significant impact on COVID-19 incidence, hospitalisation, and mortality (Upshaw et al., 2021). Average house prices were also included as another measure of local economic status. Existing literature has demonstrated that pandemic outcomes are strongly related to population density as higher density facilitates transmission (Wong and Li, 2020). To capture this effect, we used the number of people per square kilometre as a measure of local population density. Some studies have provided evidence that COVID-19 has impacted some segments of the population more than others such as minority ethnic groups and people working in certain jobs (Sze et al., 2020). Several studies have shown an increased risk of hospitalization and death due to the virus among obese people. The population age structure is also confirmed as an important risk factor (Gao et al., 2020, Hussain et al., 2020). Men have also been identified as being at higher risk of death and severity of COVID-19 infection (Zheng et al., 2020). Therefore, these variables, i.e. proportion of ethnic minority population, percentage of obese people, percentage of people working in risky jobs, median age of population, and percentage of male population in each local authority were utilised in our regression model to control for these confounding factors. In addition, we also controlled for regional effects to account for unobserved heterogeneity by incorporating regional dummy variables for 12 regions. These correspond to the Nomenclature of Territorial Units for Statistics 1 (NUTS 1) classification of the regions of the UK, comprising nine English regions and Scotland, Wales, and Northern Ireland (Eurostat, 2021). However, due to unavailability of data for Northern Ireland, our sample consists of 11 regions.

As a second approach, we applied an instrument variables strategy to deal with potential omitted variable bias. We needed to identify an instrument that is an exogenous source of variation in the ECI. First, following the strategy in Vu (2020), we employed a simple jack-knifed average of the ECI of neighbouring local authorities as a valid exogenous instrument for ECI of each local authority (Vu, 2020). The idea of this instrument is to exploit the fact that the ECI of a region's productive structure is correlated with those of neighbouring regions. For example, Bahar et al. (2014) established that neighbouring regions have more similar export baskets than more distant regions (Bahar et al., 2014). This is because neighbouring regions defined by administrative boundaries share similar knowledge and technology, so there is some spatial correlation of the ECI across regions. Other studies use a similar approach. For example, Ligon and Sadoulet (2018) used the mean of neighbouring countries' growth rates of sectoral income as an instrument for sectoral income in each country (Ligon and Sadoulet, 2018). Gründler and Krieger adopted a similar strategy to explore the impact of a country ‘s democracy on economic growth (Gründler and Krieger, 2016).

Therefore, we divided the sample into 12 distinctive UK regions, to create IV_i *for* each local authority *i* as follows:

$$IV_i = \frac{1}{N_j - 1} \sum_{z \neq i} ECI_z \qquad (2)$$

where N_j is the number of local authorities in each region j; *z* consists of neighbouring local authorities of *i*. That is, to ensure the instrument is exogenous, we defined it as a simple average of the *ECI* of neighbouring local authorities excluding the *ECI* for each local authority *i* in the calculation. Thus IV_i has no direct impact on local authority COVID-19 case and mortality rates (CM_i).

As an additional test and to provide robust results we added another external instrument in our model specifications. Existing studies provide evidence that income level has a significant impact on both COVID-19 outcomes (CM_i) (Jung et al., 2021, Tan et al., 2021) and the ECI (Lee and Vu, 2020), thus there is a possibility of income being endogenous. The inclusion of a jack-knifed average of the IMD-income average in neighbouring local authorities as another external instrument addresses this concern. Furthermore, prior studies emphasise the importance of an accurate definition of the relevant regions to obtain unbiased estimates (Vu, 2020). A wider classification of regions is more likely to eliminate the regional variation in ECI that may directly influence COVID-19 outcomes (CM_i), but it helps to reduce the correlation between the instrument variable (IV_i) and ECI_i. On the other hand, a narrower classification may increase the risk of including neighbouring local authorities that directly influence (CM_i) yet weaken the instrument (IV_i). The latter, however, limits possible weak instrument bias. Therefore, as a robustness check that our use of regions does not distort the estimates, we also applied a narrow classification based on the Nomenclature of Territorial Units for Statistics 2 (NUTS2) classification of the regions of Great Britain and split the sample into 40 distinctive regions (Eurostat, 2021).

There were two dependent variables (and two sets of regression models) in our study: the mortality rate, defined as the number of deaths per 100,000 population in each locality; and morbidity rate defined as the number of COVID-19 cases per 100,000 population in each locality. The data was obtained from UK official sources. COVID-19 mortality and morbidity data was obtained from the government's COVID-19 dashboard that updates the case numbers and mortality data for each local authority on a daily basis since the first day of the pandemic (COVID-dashboard-UK, 2021). We collected the COVID-19 data from 1st March 2020 until 1st March 2021, covering a period from the first wave and lockdown to the third lockdown, and including the rollout of the vaccine programme. Public health data regarding obesity, diabetes, smoking, physical activity, cancer and life expectancy were obtained from public health profiles provided by Public Health England and healthcare systems in Wales, Scotland, and Northern Ireland (Public-Health-England, 2021). Data regarding percentage of ethnic population, male population, percentage of people working in risky jobs (jobs that expose people to higher probability of virus transmission), population density, IMD-income average, and housing price were all obtained from the Office for National Statistics (ONS), which provides disaggregated demographic and economic data for all local authorities across the UK (nomis, 2019). All these public health and socio-demographic data were for the year 2020, the most recent available data. IMD-income average data refers to 2019 when the latest scores were reported for each local area across the UK.

Economic Complexity Index (ECI)

We calculated the economic complexity index for UK local authorities by drawing on 3 digit industrial employment data from the Business Register and Employment Survey for the year 2019 (BRES, 2019). To calculate the ECI based on these data, we followed the approach set out in Author et al (2021) and first construct a binary matrix M where the rows correspond to UK local authorities and the columns correspond to industries and the matrix entries are based on local authorities' location quotients in different industries (Author et al, 2021). Location quotients are a useful way of quantifying how concentrated a particular industry is in a location relative to the national average. The location quotient for industry j in local authority i is given by:

$$LQ_{ij} = (E_{ij} / \sum_{ij} E_{ij}) / (\sum_i E_{ij} / \sum_i \sum_j E_{ij}) \qquad (3)$$

where E_{ij} represents the number of people in local authority i employed in industry j. Here, a location quotient greater than 1 indicates that the local authority's employment share in that particular industry is greater than the national average. We populated the entries of the binary matrix M by letting $M_{ij} = 1$ if the location quotient for industry j in local authority i is greater than 1, and $M_{ij} = 0$ otherwise. A local authority's *diversity* (d_i) is defined as the number of industries that it has with a location quotient greater than 1 in (i.e. $\sum_j M_i$), while an industry's *ubiquity* (u_j) is defined as the number of local authorities that have a location quotient greater than 1 in that industry (i.e. $\sum_i M_i$).

We then calculated a local authority similarity matrix given by:

$$\widetilde{M} = D^{-1}MU^{-1}M' \tag{4}$$

where D and U are diagonal matrices formed respectively by local authority diversity values and industry ubiquity values along the diagonal. This $\widetilde{M}$ matrix captures how similar each local authorities' industrial concentrations are to another (Author et al, 2019). Finally, we calculated the economic complexity index (ECI) for UK local authorities by finding the eigenvector associated with the second largest right eigenvalue of the $\widetilde{M}$ matrix.

Radius of gyration

We considered two hypotheses concerning the drivers of the association between ECI and COVID-19 outcomes in different localities, mobility (Santana and Di Clemente, 2022, Gozzi et al., 2021, Oliver et al., 2020, Chang et al., 2021, de Castro et al., 2021) and percentage of people working in risky jobs (Sze et al., 2020). As a measure of mobility, we considered the radius of gyration for each locality. We used as the variable the change in radius of gyration pre- (March 2019 to March 2020) and post-COVID-19 (March 2020 to March 2021) (the first lockdown in UK started on 23rd of March 2020 and the last (third) one finishing in March 2021).

The mobility data in this study was collected from anonymous mobile phone users who opted-in to give access to their location data anonymously, through a General Data Protection Regulation

(GDPR) compliant framework. In addition to anonymizing the data, the data provider applied noise to sensitive areas, such as home locations, to prevent re-identification. The datasets contain records of UK users from March 2019 to early March 2021. We analyze the radius of gyration defined as (González et al., 2008):

$$RG_u = \sqrt{\frac{1}{N_u} \sum_{i=1}^{N_u} (\vec{r}_u^{\,i} - \vec{r}_u^{\,cm})^2} \quad (5)$$

where N represents the unique locations visited by the user u, $\vec{r}_u^{\,i}$ is the geographic coordinate of location I, and $\vec{r}_u^{\,cm}$ indicates the center of mass of the user trajectory. To put it simply, the radius of gyration defines the radius of the circle within which each users are more likely to be found. It is centered in all the visited locations by a user and is weighted by the number of times each location is visited. The data set analysed in this study contained mobility records of 1 billion de-identified, opted-in users. The data used was a weekly, monthly, and yearly time snapshot of the median radius of gyration of the users who resided in each single local authority.

Results

OLS regressions

Table 1 shows the results from the OLS regression analysis of the relationship between local authorities' ECI and COVID-19 morbidity and mortality rates (descriptive statistics can be found in tables A2 and A3 in appendix). For both these dependent variables, we find a negative and strongly statistically significant association after including the various control variables and regional dummies for geographical heterogeneity discussed in the methods section.

Table 1. OLS regression analysis results to investigate the association between ECI and COVID-19 morbidity and mortality rates in UK local authorities

In fact, in models 3 and 4 (in the table 1) we find that a decrease in ECI of one standard deviation (0.977) is associated with an increase of approximately 656 more COVID-19 cases and 11 more deaths per 100,000 people. The estimated coefficients for the IMD-income average are positive and statistically significant at the 1% level in all models, confirming that local authorities with higher poverty rates are more vulnerable to the disease. Notably, when we include the ECI, the magnitudes of the coefficients on this variable are lower (models 3 and 4). This emphasizes the importance of the economic structure as captured by the ECI, rather than the level of income per se.

The coefficients for ethnic groups and median age also have significant impact on COVID-19 outcomes. This implies older people and those who are not white are more likely to suffer. The negative coefficient we obtain on the proportion of male population is rather surprising and is not in line with the existing studies (Zheng et al., 2020). However, consistent with the literature we also find a higher mortality rate among obese people (Gao et al., 2020, Hussain et al., 2020).

Instrumental variables

Although our models include several local authority level control factors, we cannot rule out the possibility of omitted variable bias in our model. Therefore we used an instrumental variable approach, employing two-stage least squares. Table 2 presents the results with cluster robust standard errors and including the same set of control variables as the OLS estimates.

Table 2. ECI and COVID-19 morbidity and mortality rates. IV-2SLS estimates

Corroborating the earlier estimates, the results reveal that local economic structure has a statistically significant impact on COVID-19 outcomes: a lower ECI is associated with worse COVID-19 outcomes. The magnitudes of estimated coefficients are very close to the OLS model. Specifically, the coefficients of plausibly exogenous components of ECI in models (1 and 2 in table 2) imply that on average a one standard deviation decrease in ECI level (0.997) is associated with approximately 681 more COVID-19 cases and 13 more deaths per 100,000 population. In addition, by including a jack-knifed average of the IMD-income average in neighbouring local authorities as a second external instrument in our estimation models (3 and 4 in table 2), we reached the same conclusion, and the estimated results yield strong support for a negative relationship between ECI and COVID-19 outcomes.

We employ several tests to assess the validity of the instruments. The significant p-value of LM statistic and insignificant Hansen statistics indicates that our instruments as measured by jack-knifed avenge of ECI and income are correctly identified. Following Staiger and Stock (1997) and Stock and Yogo (2005), we test whether our model is driven by weak instrument variables (Staiger et al., 1997, Stock and Yogo, 2005). The magnitudes of Wald F-statistics are higher than the standard threshold of 10 and provide evidence that our instruments are strong and satisfy the relevant condition. Note that unreported estimates using more detailed classification of local authorities did not affect the estimated results and closely resembled the baseline findings.

Drivers of the ECI and COVID-19 association

To explain the drivers of the revealed negative association between ECI and COVID-19 cases and death, we hypothesised that the association would be stronger in localities with a higher percentage of people working in risky jobs and smaller changes in pre and post-pandemic mobility of gyration. The reason is that in low ECI areas, people are more likely to have jobs that will expose them to the virus and they are less likely to be able to reduce their mobility by working from home. Accordingly, we first tested to see if the percentage of people in risky jobs and changes in mobility were different in local authorities with different ECI. Table 3 shows a significant relationship between ECI and both percentage of people in high risk jobs and mobility changes across localities. People in the high ECI group of localities significantly reduced their mobility compared with the pre-pandemic period, and a higher proportion worked in jobs posing less risk of COVID-19 exposure (Figure A1 in the appendix illustrate the relationship between ECI and mobility changes).

Table 3. Two sample t-test to investigate the relationship between ECI and mobility changes (%) and proportion of people working in risky jobs (%)

In the next step, by repeating the previous regression model using sub-samples of mobility changes (higher mobility and lower mobility) and percentage of people in risky jobs (high, medium, and low), we explored how the revealed relationships between ECI and mobility changes and percentage of people working in risky jobs translate to COVID-19 profiles across local authorities. Table 4 shows that low ECI was linked with higher mobility (i.e. a smaller reduction in mobility during the pandemic compared to previously) and this translated to a higher rate of COVID-19 infections and deaths (Figure A2 and A3 in the appendix illustrate the relationship between mobility changes and COVID-19 cases and deaths, respectively). To be precise, as table 4 illustrates, local authorities with a lower ECI and higher mobility had 640 COVID-19 cases per 100,000 population, compared to 615 COVID-19 cases per 100,000 population in localities with higher ECI and lower mobility. Similarly for deaths, places with lower ECI and higher mobility over the pandemic time experienced 15 cases of COVID-19 deaths per 100,000 population compared with 5 for high ECI, lower mobility places. The table also reports the results for the percentage of people in high risk jobs. A lower ECI means a higher percentage of people in these jobs which translates to higher number of COVID-19 cases (858 cases per 100,000 population) and deaths (19 deaths per 100,000 population), compared to localities with a higher ECI with a lower percentage of people in risky jobs and, in turn, lower COVID-19 cases (461 cases per 100,000 population) and deaths (9 cases per 100,000 population). These findings corroborate our hypotheses that the reason for higher rates of COVID-19 cases and deaths in local authorities with a lower ECI is that people in these areas were more exposed to the virus because of the nature of their jobs, for which they travelled higher distances from home (some even travelling greater distances than they used to before the pandemic) while people in high ECI local authorities were more able to work from home and travel less.

Table 4. OLS regression analysis results investigating the association between ECI and COVID-19 profile in UK local authorities through the channels of mobility changes and proportion of people in risky jobs

We also explored whether these relationships changed over time, comparing different periods of lockdown and easing of restrictions in the UK (Table 5). The results indicate that the relationship of ECI with COVID-19 cases and deaths was consistent over the period of time considered (Figure A4 in the appendix illustrates the consistent pattern of changes in mobility in different ECI quantiles over the course of the pandemic).

Table 5. OLS regression analysis results to investigate the association between ECI and COVID-19 morbidity and mortality rates in UK local authorities over pandemic time

Finally, we also explored how economic complexity is associated with other common public health indicators, using similar methodology. The findings showed that economic complexity was significantly negatively correlated with cardiovascular mortality, diabetes rate, and smoking rate at delivery, and positively with the physical activity rate (Table 6). While not pursuing these further in this study, they point to future avenues for research concerning economic complexity and public health outcomes as it seems that ECI plays a significant role in shaping the health of the population above and beyond income and other economic indicators that are normally used in public health literature to investigate the relationship between public health indicators and economic conditions at place levels.

Table 6. OLS regression analysis results to investigate the association between ECI and some public health outcomes in UK local authorities

Discussion

This study has explored the role of economic structure in shaping COVID-19 morbidity and mortality rates of local communities in the UK by applying the lens of economic complexity. Our contribution is to show that differences in economic structure as measured by the ECI is significantly associated with the pandemic (public health) outcomes of the local population, beyond the impact of socio-economic variables considered separately. We identified the channel as being the proportion of people in jobs involving contact with others, and thus the extent to which people were able to reduce their mobility and stay home after the onset of the pandemic. These variables are strongly associated with local authorities' ECIs. The places people live, given their socio-economic structure, shape COVID-19 outcomes.

These findings enrich the nascent field of economic complexity and population health literature by integrating COVID-19 and other public health measures into the picture at a sub-national level (Innocenti et al., 2021, Vu, 2020). UK local authorities with low ECI, which tend to have employment concentrated in less knowledge-intensive activities (agriculture, mining and low-value manufacturing), experienced worse COVID-19 mortality and morbidity rates (as well as cardiovascular mortality, diabetes rate, physical activity, and smoking status). The implication is that COVID-19 and other health outcomes are a systemic phenomenon related to the character of the places in which people live, and should be dealt with accordingly.

A number of studies so far have investigated the influence of several local economic characteristics on COVID-19 outcomes. For instance, Mena and colleagues used an index called Social Priority Index (SPI) to investigate the differences between 34 municipalities of Santiago in Chile in terms of COVID-19 mortality and morbidity rates and showed that municipalities of lower socioeconomic status suffered more (Mena et al., 2021). The SPI index combined three measures of income, education, and life-expectancy, measured at the individual level but used as proxies to judge community-level socio-economic status.

In another study in Brazil, Rocha and colleagues used a similar proxy index called Social Vulnerability Index (SVI) at state level to investigate the differences in initial spread of the virus, death rate, and effectiveness of epidemic containment policies (Rocha et al., 2021). The state-level SVI was calculated using a principal components analysis (PCA) of the percentage of households in vulnerable housing conditions, the share of informal workers by state, and the income and education subcomponents of the Human Development Index (HDI). The study showed that the initial spread of the virus across the states was mostly determined by social vulnerability status, rather than age structure and proportion of people with chronic health conditions, disfavoring the poor states. Mortality rates were also higher among states with a poor SVI, at least in the early phases of the pandemic. In another study from Brazil, inspired by the global multidimensional poverty index, Tavares and Betti constructed a regional Multidimensional Vulnerability Index (MVI) in order to reveal state-level differences in COVID-19 infection and mortality rates (Tavares and Betti, 2021). The COVID-19 specific MVI was a combination of the following indices at state levels: proportion of households with no proper access to drinking water, sanitation, electricity, proportion of households with school meals for their children, share of food from total household expenditure, proportion of overcrowded households, average commuting-to-work time, population density, and two indices of mobility and social distancing that were developed to rank states in terms of adopted COVID-10 containment regulations. The study revealed that states with worse MVI were more vulnerable to the virus and could not adopt the required containment strategies as well as their better-off counterparts.

In related studies in the US, a Social Vulnerability Index (SVI) was used to examine the association between community-level vulnerabilities and COVID-19 morbidity and mortality rates at different geography levels and at different times over the pandemic (Neelon et al., 2020, Islam et al., 2021, Oates et al., 2021). The SVI is a percentile-based measure of social vulnerability, comprising four dimensions of various aspects of vulnerability, including socioeconomic status, household composition, race/ethnicity/language, and housing/transportation each consisting of variables that provide a score between 0 to 1 for each theme and for the overall SVI at county levels. Higher scores of the SVI indicate higher vulnerability. Two recent studies used a longitudinal approach (Neelon et al., 2020, Islam et al., 2021). They showed that the SVI is a strong and independent predictor of COVID-19 morbidity and mortality, disfavoring the less-resilient communities; its contribution weakened as the time passed until winter 2020, but gained traction again in summer 2021. Another recent study from the US, however, showed that hospitalization and rate of severe COVID-19 cases were not associated with the Area Deprivation Index (ADI), which is similar to the SVI (Ingraham et al., 2021).

Three studies from the UK have also shown that area deprivation is a strong predictor of COVID-19 incidence, hospitalization, and mortality after controlling for various cofounders (Williamson et al., 2020, Patel et al., 2020, Niedzwiedz et al., 2020). The Index of Multiple Deprivation (IMD), Townsend deprivation index, and educational level at area levels have been used as the proxies for area-level socioeconomic status. The IMD and Townsend index are similar to the composite indices used in the above-mentioned studies as they combine data on income, employment, housing, and related factors to rank and compare the localities according to their deprivation status. A similar finding is also reported from a megacity in India, Chennai, where an area-level index of multiple deprivations (IMD) was developed to investigate the spatial pattern of COVID-19 distribution across the city electoral wards (Das et al., 2020).

All these findings are, for the most part, consistent with our finding that local authorities with lower ECI suffered more intensively. However, our measure of economic complexity improves on the various composite vulnerability and deprivation indices used in the above-mentioned studies, for it summarizes the entire underlying economic structure of a locality.

This structural aspect is intuitive as COVID-19 is an infectious respiratory disease, hence differences in unavoidable contact via work and collective human mobility will be a factor determining its concentration in some localities. Our data is consistent with other evidence that there has been less reduction in collective mobility in areas with lower socioeconomic status in several countries over the course of the pandemic (Chang et al., 2021, Castro et al., 2021, Mena et al., 2021, Valdano et al., 2021). Other factors might help explain the association between economic complexity and COVID-19 outcomes. For example, some studies have shown that public health campaigns regarding mask wearing, hand hygiene, and household bubbles during the pandemic found less compliance among groups of lower socioeconomic status (Paremoer et al., 2021, Upshaw et al., 2021, Castro et al., 2021). Fundamentally, though, people of different socioeconomic status have to respond differently to COVID-19 restrictive policies because of the characteristics of their jobs, for people with jobs that cannot be done from home (retail, hospitality, food, administrative, services, etc.) tend to live in low ECI areas. They have to travel to work and this greater mobility then translates to higher virus transmission in these areas. To the best of our knowledge, there has been no prior research to investigate the relationship between economic complexity and collective mobility patterns.

The underlying mechanisms driving the significant relationship we have identified require further study. For instance, another mediating factor that could help explain the association between economic complexity and COVID-19 outcomes relates to differences in the quality of health services across the UK local authorities. Although the UK has a publicly-funded national health system, previous research has shown that there are considerable differences between localities in terms of the quality of health services, favouring the better-off localities (Asaria et al., 2016, Scobie and Morris, 2020). Therefore, considering the fact that higher economic complexity can lead to better healthcare services and human capital, differences in health services quality as in complexity of the economic structure among local authorities may be relevant to our findings.

What is clear from our findings, however, is that differences in local economic structure as captured by the ECI not only have implications for places' economic performance (Author et al, 2021), but also strongly affect public health outcomes. If the ambitions to 'level up' places are to succeed, health and economic policies will need to be integrated and focused on deep-seated aspects of economic structure (Bambra and Lynch, 2021).

Conclusion

Using the lens of economic complexity, our study has shown that differences in the structure of the economy in UK local authorities as captured by the economic complexity index is strongly associated with differences in COVID-19 outcomes. The channel for the link is the change in mobility in different areas, corresponding to the types of jobs that characterize them. Lower ECI local economies have fared worse than higher ECI ones in dealing with the pandemic. The results suggest the need for coordination of economic and health policies to address inequalities between places in a systemic and effective way.

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Disclosure statement.

The authors report there are no competing interests to declare.

Data availability.

Some of the data that support the findings of this study are available in [Public Health Outcomes Framework; UK COVID-19 dashboard; Local Authority Profile] at [Public Health Outcomes Framework - GOV.UK (www.gov.uk); Download data | Coronavirus in the UK; Labour Market Profile - Nomis - Official Labour Market Statistics (nomisweb.co.uk)], reference number [(Public-Health-England, 2021, COVID-dashboard-UK, 2021, nomis, 2019)].

Mobility data are available from Cuebiq. Restrictions apply to the availability of these data. Data are available from the corresponding author with the permission of Cuebiq.

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Table 1.

	COVID-19 cases		COVID-19 deaths	
	(1)	(2)	(3)	(4)
ECI		-656.270***		-11.875***
		(0.000)		(0.010)
IMD-income average	6765.609***	4248.621*	518.312***	456.090***
	(0.002)	(0.052)	(0.000)	(0.000)
Cost of housing	-0.098	0.055	-0.008***	-0.005**
	(0.175)	(0.533)	(0.000)	(0.034)
Population density	0.020	0.017	0.001	0.001
	(0.399)	(0.457)	(0.467)	(0.497)
Ethnic groups	44.761***	44.464***	0.394	0.356
	(0.000)	(0.000)	(0.265)	(0.304)
Percentage of people working in risky jobs	52.322***	27.041*	0.499	0.187
	(0.000)	(0.100)	(0.278)	(0.720)
Percentage of adults with obesity	-5.689	-5.579	0.069	0.035
	(0.368)	(0.467)	(0.723)	(0.872)
Median age	-173.578***	-219.626***	1.187	0.269
	(0.000)	(0.000)	(0.140)	(0.766)
Male population (%)	-59177.467***	-55145.036***	-1629.488***	-1575.170***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	37958.841***	38519.194***	849.240***	868.077***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	326	326	305	305
Regional fixed effect	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y
R-squared	0.683	0.710	0.491	0.504

Notes: This table reports the regression results to assess the impact of the control variables and ECI on COVID-19 mortality rate and the number of cases. The specifications are estimated by OLS regression.
Variable definitions are presented in appendix A. Robust standard errors adjusted for clusters in local authorities are in parentheses.
***, **, * denote the significance level at 1%, 5%, and 10%, respectively

Table 2.

	Jack-knifed regional average of ECI		Jack-knifed regional average for ECI and Income	
Variables	COVID-19 cases	COVID-19 death	COVID-19 cases	COVID-19 death
	(1)	(2)	(3)	(4)
Panel A. Second-stage estimates. Dependent variables are COVID-19 cases and deaths respectively				
ECI	-681.793***	-13.387***	-694.904***	-13.535***
	(0.000)	(0.006)	(0.000)	(0.005)
Panel B. First-stage estimates. Dependent variable is ECI				
IV	-21.067***	-21.068***	-21.150***	-21.155***
	(0.000)	(0.000)	(0.000)	(0.000)
Baseline controls	Y	Y	Y	Y
Constant	Y	Y	Y	Y
Regional fixed effect	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y
Observations	326	305	326	305
R-squared	0.709	0.504	0.710	0.504
F-test	42.819	37.367	40.022	37.12
Kleibergen-Paap Wald test	44.34	40.40	23.10	20.68
Cragg-Donald Weak identification test	808.09	720.31	405.69	361.37
Kleibergen-Paap LM statistic Under identification test (p-value)	0.000	0.000	0.000	0.000
Hansen J statistic Over-identification test (p-value)	n/a	n/a	0.386	0.443

Notes: This table presents instrumental variables (IV-2SLS) estimates of the effects of economic complexity on COVID-19 mortality rate and cases. Baseline controls are the main control variables included in Table 1. Instrument variable is a jack-knifed regional average of ECI in columns 1&2. We add a second instrument of a jack-knifed regional average of income in columns 3&4.The F-test provided the F-statistic for the joint significance of the instruments in the first stage. The Kleibergen-Paap Wald test is under the null hypothesis that the instruments are weakly correlated with the endogenous regressors. In addition, the rejection of this null should be based on Cragg-Donald Wald critical values as follow: 16.38 (10% maximal IV size), 8.96 (15% maximal IV size), 6.66(20% maximal IV size), 5.53 (25% maximal IV size) for one instrument; and the following for the use of two instruments : 19.93 (10% maximal IV size), 11.59 (15% maximal IV size), 8.75 (20% maximal IV size), and 7.25 (25% maximal IV size). Kleibergen-Paap LM statistic and Hansen J statistic give the p-value of the test for under-identification and over-identification. The estimated parameters of control variables are excluded to save space.

Variable definitions are presented in appendix A. Robust standard errors adjusted for clusters in local authorities are in parentheses.

***, **, * denote the significance level at 1%, 5%, and 10%, respectively.

Table 3.

Variables	ECI quantiles	1	2	3	t-test
Mobility change (%)	Mean	-29.194%	-34.279%	-37.613%	16.001***
Proportion of people working in risky jobs (%)	Mean	29.703	26.552	22.121	67.001***

Notes. This table reports the mean value of interested variables based on different quantile of ECI. Local authorities are grouped into 3 quintiles based on ECI value. Group 1 has the lowest value of ECI and group 3 has the highest value. We report t statistics and p-value for differences in mean of variables in q1 vs q3. *, **, and *** shows statistical significance at the 10%, 5%, and 1% level, respectively.

The definitions of all variables are provided in Table A1 of Appendix.
Mobility change (%) is the difference between mobility pre (March 2019 to March 2020) and post (March 2020 to March 2021) pandemic divided by pre-pandemic (March 2019-March 2020) mobility multiplied by 100.

Table 4.

Panel A. Channel analysis for mobility changes				
	COVID-19 cases		Covid-19 deaths	
	Higher mobility	Lower mobility	Higher mobility	Lower mobility
	(1)	(2)	(3)	(4)
ECI	-639.465***	-615.973***	-15.006***	-5.353
	(0.000)	(0.001)	(0.007)	(0.485)
Baseline controls	Y	Y	Y	Y
Constant	Y	Y	Y	Y
Regional fixed effect	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y
R-squared	0.761	0.755	0.547	0.527

Panel B. Channel analysis for proportion of people in risky jobs						
	Low risky jobs	Medium risky jobs	High risky jobs	Low risky jobs	Medium risky jobs	High risky jobs
	(1)	(2)	(3)	(4)	(5)	(6)
ECI	-460.615**	-499.608**	-858.352***	-9.365	-12.718	-18.658*
	(0.010)	(0.024)	(0.000)	(0.105)	(0.111)	(0.087)
Baseline controls	Y	Y	Y	Y	Y	Y
Constant	Y	Y	Y	Y	Y	Y
Regional fixed effect	Y	Y	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y	Y	Y
R-squared	0.674	0.818	0.803	0.616	0.611	0.548

Note: This table presents the results from a channel analysis of the relationships between ECI, mobility changes, risky jobs percentage, and COVID-19 morbidities and mortalities.

Higher mobility means that there was no, a little reduction, or even increase in the mobility post COVID-19, compared to the pre COVID-19 time. Lower mobility means that there was high and considerable reduction in mobility post COVID-19, compared to the pre-COVID-19 period.

The percentage of people in risky jobs is also divided into three groups of localities: low, medium, and high.

Table 5.

Variables	COVID-19 cases					COVID-19 deaths				
	1st Lockdown	No Lockdown	2nd Lockdown	No Lockdown	3rd Lockdown	1st Lockdown	No Lockdown	2nd Lockdown	No Lockdown	3rd Lockdown
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI	-649.738***	-659.211***	-659.211***	-659.211***	-658.421***	-11.895***	-11.761**	-11.761**	-11.761**	-12.148***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.011)	(0.012)	(0.012)	(0.008)
Baseline controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Regional fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.710	0.711	0.711	0.711	0.710	0.505	0.504	0.504	0.504	0.501

Note:
First lockdown time: 23rd March 2020 to 23rd June 2020;
Second lockdown time: 31st October 2020 to 2nd December 2020;
Third lockdown time: 6th January 2021 to 8th March 2021.

Table 6.

Variables	(1) Mortality rate-Cardiovascular	(2) Mortality rate Cancer	(3) Cancer rate	(4) Diabetes rate	(5) Physical activity rate	(6) Smoking rate at delivery	(7) Life expectancy
ECI	-2.123**	-0.503	0.047	-4.125***	1.781***	-0.937***	-0.147
	(0.038)	(0.614)	(0.900)	(0.000)	(0.000)	(0.000)	(0.229)
IMD-income average	220.276***	282.883***	-32.647***	8.825	-44.422***	43.987***	-15.856***
	(0.000)	(0.000)	(0.000)	(0.537)	(0.000)	(0.000)	(0.000)
Cost of Housing	0.001	-0.000	0.000	0.000	0.000	-0.000	0.000*
	(0.230)	(0.647)	(0.661)	(0.939)	(0.332)	(0.543)	(0.097)
Population density	-0.000	-0.000	0.000**	0.000	-0.000*	-0.000**	0.000
	(0.446)	(0.296)	(0.016)	(0.377)	(0.093)	(0.033)	(0.146)
Ethnic groups	-0.036	-0.560***	0.008	0.069	-0.152***	-0.115***	0.010
	(0.672)	(0.000)	(0.821)	(0.306)	(0.000)	(0.000)	(0.306)
Percentage of people working in risky jobs	0.359***	0.265***	0.022	0.282***	-0.190***	0.043	-0.010
	(0.006)	(0.010)	(0.629)	(0.001)	(0.000)	(0.176)	(0.479)
Percentage of adults with obesity	-0.174**	-0.186***	-0.012	-0.054	0.068**	-0.003	0.020
	(0.025)	(0.002)	(0.705)	(0.248)	(0.020)	(0.775)	(0.132)
Median age	-0.634***	-1.517***	-0.053	-0.489***	0.179**	-0.005	
	(0.000)	(0.000)	(0.428)	(0.001)	(0.037)	(0.915)	
Male population	127.198**	-23.569	-16.156	8.482	58.217*	-6.426	
	(0.037)	(0.703)	(0.600)	(0.882)	(0.070)	(0.305)	
Constant	6.326	182.684***	68.547***	89.083***	38.859**	7.060***	84.250***
	(0.847)	(0.000)	(0.000)	(0.004)	(0.027)	(0.005)	(0.000)
Observations	271	271	271	271	270	270	270
Regional fixed effect	Y	Y	Y	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y	Y	Y	Y
R-squared	0.836	0.847	0.310	0.417	0.558	0.748	0.648

Notes: This table reports the regression results to assess the impact of the control variables and ECI on different health outcomes. The specifications are estimated by OLS regression. Variable definitions are presented in Table A1. Robust standard errors adjusted for clusters in local authorities are in parentheses. ***, **, * denote the significance level at 1%, 5%, and 10%, respectively.

Appendix A

Table A1. Variable Definitions

Ethnic group%: percentage of ethnic population in each local authority.
Percentage of adults (aged 18+) classified as overweight or obese: percentage of people over 18 years old with a body mass index (BMI) of over 25.
Percent of active people working in COVID-19 risky jobs: percentage of people who work in the following jobs in each local authority: elementary occupations (include processing plant workers, security guards, chefs and taxi drivers) and caring, leisure and other service occupations. These people are at higher risks of COVID-19 infection and mortality.
Population density: population per square kilometer in each local authority.
Index of Multiple Deprivation (IMD)-income average: It is a domain in the IMD that measures the proportion of the population experiencing deprivation relating to low income.
Cost of housing: Amount of money (£) each family in the UK pays for housing (out of their income) in the UK annually.

Table A2. Descriptive statistics.

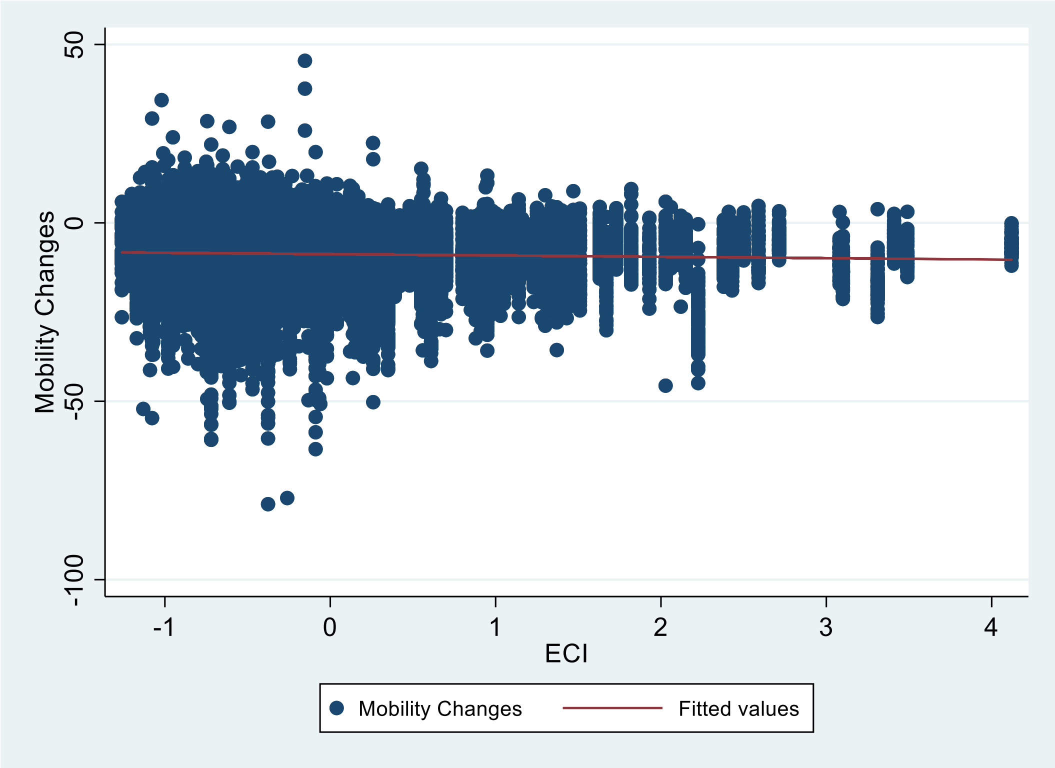
Variables	Observation	Mean	Std. Dev.	Min	Max
COVID-19 cases	355	5816.341	2067.807	314.300	11267.500
COVID-19 deaths	334	187.781	61.645	13.500	376.200
ECI	357	-0.015	0.977	-1.260	4.120
Income Average-IMD	364	0.100	0.059	0.000	0.251
Cost of Housing (3)	364	2993.297	2021.496	5958	10650
Population density	364	1624.879	2529.124	9.000	16237
Ethnic group	364	9.846	12.470	0.000	71.000
Percentage of active people working in risky jobs	341	26.417	6.458	9.940	55.110
Percentage of adults with obesity	364	53.639	23.030	0.000	75.950
Median age	364	42.498	4.974	28.900	54.300
Male population	364	0.488	0.009	0.466	0.537

As the table show, on average, there were 5816 and 187 cases and deaths, respectively, due to COVID-19 in the local authorities of the UK (from March 2020 to March 2021).

Table A3. Correlation Matrix.

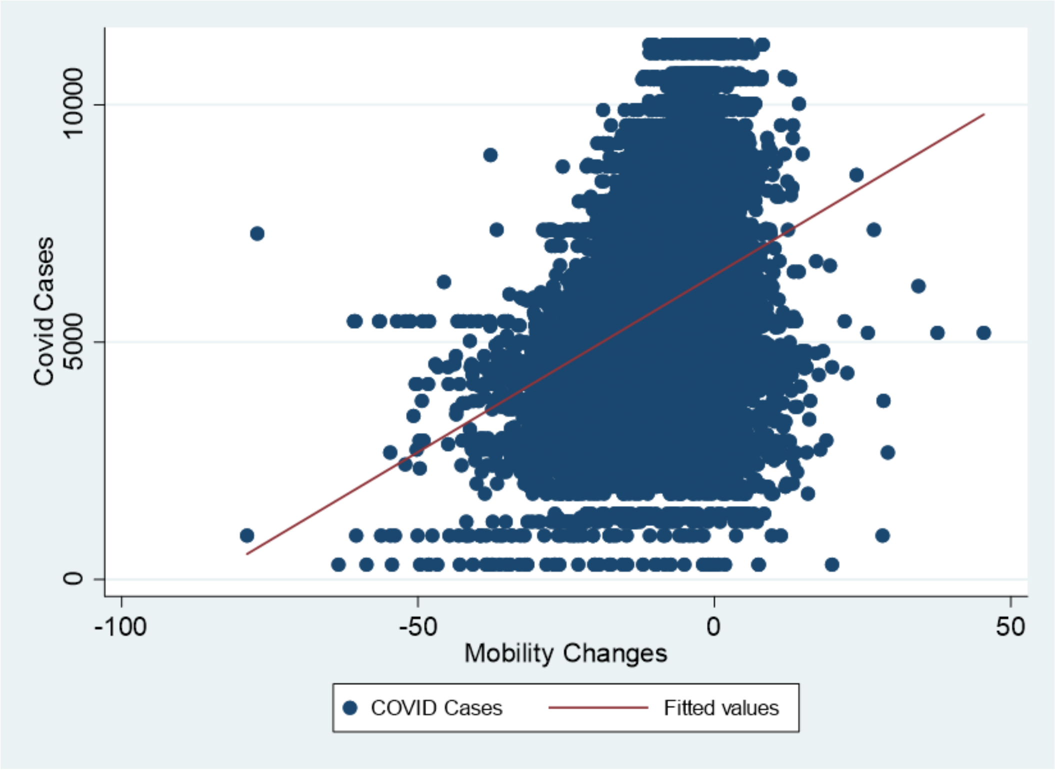
	Variables	A	B	C	D	E	F	G	H	I	J	K
A	COVID cases	1.000										
B	COVID death	0.647	1.000									
C	ECI	-0.150	-0.240	1.000								
D	Income Average-IMD	0.655	0.470	0.043	1.000							
E	Cost of Housing	0.323	0.025	0.486	0.230	1.000						
F	Population	0.177	0.089	0.044	0.049	0.050	1.000					
G	Ethnic group	0.566	0.055	0.564	0.401	0.460	0.075	1.000				
H	% People Working-Risky	0.119	0.187	-0.512	0.286	-0.230	-0.096	-0.158	1.000			
I	%Adults aged18-obese	0.350	0.295	0.080	0.615	0.192	0.049	0.243	-0.028	1.000		
J	Median age	-0.577	-0.019	-0.611	-0.386	-0.428	-0.097	-0.682	0.053	-0.097	1.000	
K	Male population	0.216	-0.116	0.337	0.260	0.210	0.007	0.516	0.049	0.201	-0.513	1.000

Figure A1. The relationship between mobility changes (before and after the pandemic) and ECI



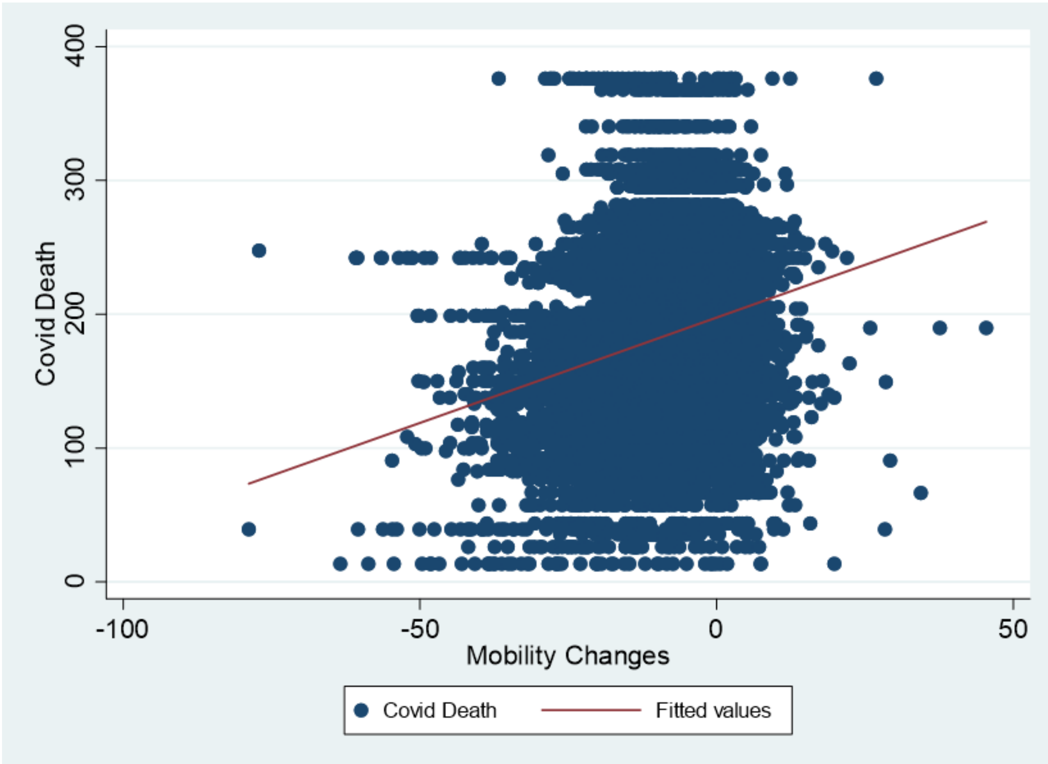
The figure shows that as one moves towards localities with higher ECI, the changes in mobility (the difference between radius of gyration before and after the pandemic) gets under 0 in almost all these localities, indicating that people in these regions had reduced their radius of gyration after the pandemic (they stayed and worked from home). In contrast, although we see that the overall trend of mobility change was below 0 in the localities with lower ECI, i.e. people in these region also reduced their radius of gyration, but there are a considerable number of localities that show no change or a positive mobility change, i.e. people in these regions even had higher radius of gyration after the pandemic, which can be translated to higher chance of contact with COVID-19 virus.

Figure A2. The relationship between COVID-19 cases and mobility changes



This graph shows that as the mobility changes becomes positive, i.e. people have higher radius of gyration after the pandemic, the number of COVID-19 cases increases sharply in the localities.

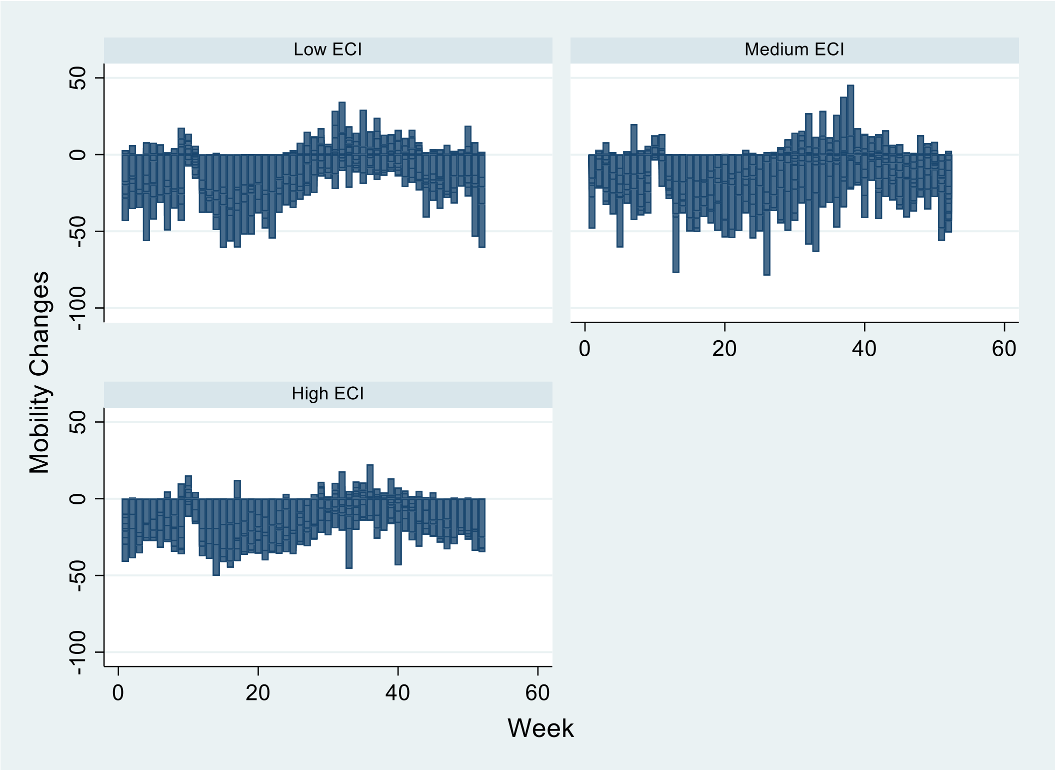
Figure A3. A graphical illustration of relationship between COVID deaths and mobility changes



This graph shows that as the mobility changes becomes positive, i.e. people have higher radius of gyration after the pandemic compared to the time before pandemic, the number of COVID-19 deaths increases significantly in the localities.

We should remember that COVID-19 is an infectious respiratory disease and human contact is the most important factor in terms of the risk of transmission and where the contact increases, to whatever reason (especially occupation), the number of cases and death increases undoubtedly.

Figure A4. Mobility changes in different ECI quntiles over the course of the pandemic



This graph shows that, generally speaking, the mobility changes (i.e. difference between radius of gyration after and before the pandemic) in the localities stayed almost the same over the pandemic course and people living in the localities with higher ECI had a consistent reduction in radius of gyration over the pandemic course, in contrast to people living in localities with lower ECI who had less reduction in their radius of gyration.