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

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Abstract

The present study investigates the association between the economic complexity of local authorities in the UK and their COVID-19 morbidity and mortality rates. We find that localities with a lower economic complexity index (ECI) registered significantly higher numbers of COVID-19 cases and deaths, controlling for a range of confounders. This result indicates that local economic structures in the UK shape people's pandemic (and public health) experiences. This finding calls for the integration of public health and economic strategies in each locality when planning economic recovery in the context of aims to reduce spatial inequalities.

Keywords: COVID-19, Economic complexity, Local authorities, Place, Mortality, Morbidity, UK

Introduction

It was clear from the early days of the COVID-19 pandemic that its incidence was unequal (Li et al., 2021; Saban et al., 2021; Upshaw et al., 2021; Valdano 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; Neelon et al., 2020; Upshaw et al., 2021; Williamson et al., 2020). 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 (Burström & Tao, 2020; Castro et al., 2021; Chang et al., 2021; 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 (Marmot, 2020; Saban et al., 2021). 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 (Marmot, 2020; Upshaw et al., 2021).

However, despite the fact that the role of socio-economic factors in COVID-19 outcomes has become increasingly clear, attention has largely focused on separate characteristics related to individuals such as income, education, smoking or obesity (Upshaw et al., 2021; Williamson et al., 2020). The contribution of the present study is to show, by contrast, that the *structure* of the socio-economic environment in which individuals live and work, as measured and described by economic complexity, is significantly associated with COVID-19 outcomes. The implication is that addressing the unequal social incidence of the disease - and indeed any future pandemics - cannot be addressed by tackling separate characteristics or risk factors. The challenge is a systemic one.

Measures of economic complexity provide a novel lens on the structure and distribution of economic activities across places, and have 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 best capture the similarities in their productive capabilities (Hidalgo, 2021)(Author et al, 2019). At the country level, countries ranking high on the Economic Complexity Index (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 (Hausmann 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 been almost barren of such investigations, even though the effects of community-level socio-economic status on health have always been acknowledged as an important factor (Marmot, 2020). In the only study published so far, Vu (2020) showed that complexity of economic structure at country level is a strong predictor of differences in life-expectancies and neonatal, infant, and under-5 mortalities (Vu, 2020). They 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. In fact, economic complexity co-evolves with institutional transformations by which employees in more complex economies can ensure they achieve rights that lead to more egalitarian societies with better healthcare coverage and population health outcomes. Third, it is postulated that economies that rank high in complexity are more resilient than less complex ones to external shocks. There is a strong relationship between economic shocks and population health outcomes. 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 previously established between better population health outcomes and human capital capabilities and productivity, as the latter translates to higher quality healthcare.

In the present study we contribute to this nascent field by investigating 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 for the reasons just set out. Our finding that the structure of a locality as summarised in economic complexity 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 rather than addressing them separately.

Methods

To examine the link between economic complexity and COVID-19 morbidity and mortality rates, we estimated 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 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 (Emami et al., 2020; Sze et al., 2020; Upshaw et al., 2021; Williamson et al., 2020; Zheng et al., 2020). To be precise, we examined the impact of deprivation status, measured by the index of multiple deprivation (IMD), 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 & 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. For example, there is strong evidence that minority ethnic groups and people working in certain specific jobs are at increased risk of death from COVID-19 (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. In order to do so, 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 dependence of 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 & Sadoulet, 2018). Gründler and Krieger adopted a similar strategy to explore the impact of a country ‘s democracy on economic growth (Gründler & 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 outcome (CM_i) (Jung et al., 2021; Tan et al., 2021) and ECI (Lee & Vu, 2020), thus It would be misleading to ignore the possibility of income being endogenous in our models. The inclusion of a jack-knifed average of the IMD index in neighbouring local authorities as another external instrument can address 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, to 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).

Variables and data

The data was obtained from UK official sources. COVID-19 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 March 2020 until February 2021. 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 score, 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 2019, as they are the most recent available data. IMD data refers to 2015 when the latest scores were reported for each local area across the UK.

There were two dependent variables (and as a result two 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.

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 b:

$$LQ_{ij} = (E_{ij} / \sum_{ij} Eij) \;/\; (\sum_{i} Eij / \sum_{i} \sum_{j} Eij) \tag{3}$$

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:

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

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.

Results

OLS Regression

Table 1 shows the results from the OLS regression analysis of the relationship between local authorities' ECI and COVID-19 morbidity and mortality rates. 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.

In fact, in models (3&4) we find that a decrease in ECI of one standard deviation (0.977) is associated with an increase of approximately 735 COVID-19 cases and 13 more deaths per 10,000 people. The estimated coefficients for the IMD index as a proxy for income 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 income are lower (Models 3&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. However, the mortality rate for older people is higher when we do not include the ECI. Similarly, the positive coefficient on proportion of people working in risky jobs on COVID-19 outcomes disappears when we include ECI. 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 variable regressions

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 instrument variable approach and employed two-stage least squares. Table 2 presents the results for IV regression models with cluster robust standard errors and including the same set of control variables as the OLS estimates. The first stage regressions are reported in figure 1, where our dependent variable is ECI. In contrast with Vu (2020) we find that our IV has a negative and significant impact on ECI (Vu, 2020). This may imply differences in the impact of ECI at the local authority level and the country level.

Corroborating the earlier estimates, the results in figure 2 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 &2) imply that on average a one standard deviation decrease in ECI level (0.997) is associated with approximately 718 more COVID-19 cases and 12 more deaths per 10,000 population. In addition, by including a jack-knifed average of the IMD index in neighbouring local authorities as a second external instrument in our estimation models (3&4), 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 the work of 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 & 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.

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 associated with cardiovascular mortality, diabetes rate, and smoking rate at delivery, and positively with the physical activity rate.

Discussion

This study aimed to unveil the role of economic structure in shaping COVID-19 morbidity and mortality rates of local communities in the UK by applying a complexity lens. Our unique contribution is to show that differences in economic structure as measured by economic complexity is significantly associated with the pandemic (public health) outcomes of the local population, beyond the impact of socio-economic variables considered separately. This enriches 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. 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 and should be dealt with accordingly.

A small number of studies so far have investigated the influence of local economic structure on COVID-19 outcomes, taking different approaches. 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 was a combination of three measures of income, education, and life-expectancy that are 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 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) on 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, and not the 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. Stringent preventive policies in the states with high SVI, however, evened out the outcomes as time passed during 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 & 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 the inequality in COVID-19 incidence and mortality rates across the states in Brazil; states with worse MVI were starkly vulnerable to the virus and could not adopt the required containment strategies as well as their better-off counterparts.

In related studies conducted 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 (Islam et al., 2021; Neelon et al., 2020; Oates et al., 2021). The SVI is a percentile-based measure of social vulnerability, or the resilience of communities to face stressors to health emanating from external hazards (e.g., natural disasters or disease outbreaks). The SVI comprises four themes that measure various aspects of vulnerability, including socioeconomic status, household composition, race/ethnicity/language, and housing/transportation. There are a couple of variables under each theme 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. The overall finding from these studies was that the SVI was a predictor of COVID-19 mortality rates, disfavouring the counties/states with poor SVI, but the incidence rate showed a varying association. Two recent studies aimed to resolve the inconsistencies in the previous studies by using a longitudinal approach (Islam et al., 2021; Neelon et al., 2020). 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 very close to the SVI in terms of composition (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 that persists after controlling for various cofounders (Niedzwiedz et al., 2020; Patel et al., 2020; Williamson et al., 2020). The Index of Multiple Deprivation (IMD), Townsend deprivation index, and educational level at area levels were used as the proxies for area-level socioeconomic status. The IMD and Townsend index are similar to indices used in 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). The findings revealed that there was a stark inequality in the number of cases across the city wards, disfavouring the ones with poor IMD.

All these findings are, for the most part, consistent with our findings that local authorities with lower ECI suffered more intensively. However, our measure of economic complexity improves on the various ad hoc vulnerability and deprivation indices used in the above-mentioned studies, for it summarizes the whole underlying economic structure of a locality. However, the finding that economic complexity is so strongly and negatively associated with unequal COVID-19 outcomes requires careful consideration, beyond the hypotheses, described above, proposed by Vu about the relationship between public health and economic complexity. As COVID-19 is an infectious respiratory disease, differences in collective human mobility will be a factor determining its concentration in some localities. There is 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, mainly due to the nature of jobs and people's leisure habits in these areas (Castro et al., 2021; Chang et al., 2021; Mena et al., 2021; Valdano et al., 2021). In fact, people of different socioeconomic status respond differently to COVID-19 restrictive policies, especially due to the job market structure, for people with low-skilled jobs (retail, hospitality, food, administrative, services, etc.) tend to live in disadvantaged areas. This factor, greater mobility, then translates to higher virus transmission in these areas. To the best of our knowledge, there has been no research to investigate the relationship between economic complexity and collective mobility patterns so this possible link requires further research. It may be that local authorities with lower economic complexity are more concentrated on economic activities that cannot be done from home such that lockdown policies were less effective in reducing mobility in those areas, giving the virus more chance to transmit. Another factor that might explain the association between economic complexity and COVID-19 outcomes is health-related knowledge and behaviour. Studies have shown that public health campaigns regarding mask wearing, hand hygiene, and household bubbles during the pandemic were not equally accepted by different socioeconomic groups, with groups of lower socioeconomic status being less compliant (Castro et al., 2021; Paremoer et al., 2021; Upshaw et al., 2021). It could be again postulated that less economic complexity is related to less accumulated knowledge about health behaviour issues, which can translate to higher rates of virus transmission.

A further 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 & 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.

These postulates about the underlying mechanism require further study. What is clear from our findings is that differences in local economic structure not only has implications for places' economic performance (Author et al, 2021), it also strongly corresponds to public health outcomes. If the UK Government's ambition to 'level up' places is to succeed, it will need to develop integrated health and economic policies.

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, along with other public health indicators. 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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Appendix

Figure 1. Raw correlations: ECI and number of deaths

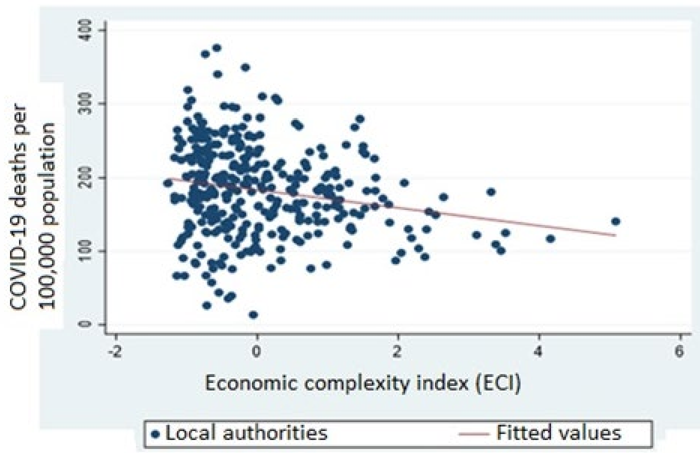

Figure 2. Raw correlations: ECI and number of cases

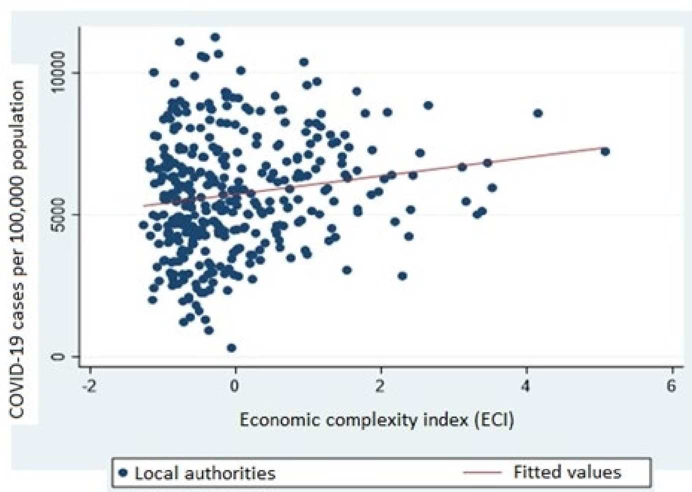

Table 1. OLS regression analysis results to investigate the association between ECI and COVID-19 morbidity and mortality rates in UK local authorities

	(1)	(2)	(3)	(4)
Variables	COVID-19 cases	COVID-19 cases	COVID-19 death	COVI19 death
ECI		**-735.59*****		**-13.96****
		(114.257)		**(4.468)**
IMD index	7,621.97***	5,302.19***	445.74***	388.49***
	(2,144.218)	(2,027.471)	(93.562)	(92.627)
Cost of housing	0.02	0.14***	-0.00	0.00
	(0.062)	(0.048)	(0.002)	(0.002)
Population density	0.02	0.02	0.00	0.00
	(0.024)	(0.023)	(0.001)	(0.001)
Ethnic groups	49.11***	49.18***	0.54	0.53
	(11.680)	(10.337)	(0.379)	(0.359)
Percentage of people working in risky jobs	39.92***	8.50	0.17	-0.31
	(12.509)	(12.586)	(0.506)	(0.555)
Percentage of adults with obesity	6.56	6.70	0.47*	0.43*
	(5.816)	(4.827)	(0.260)	(0.258)
Median age	-157.71***	-214.89***	1.78*	-0.10
	(22.543)	(23.453)	(0.918)	(0.953)
Male population	-59,289.98***	-53,655.50***	-1,640.80***	-1,562.01***
	(10,981.950)	(10,152.309)	(337.977)	(327.109)

Constant	37,605.63***	37,998.02***	861.54***	884.61***
	(5,699.642)	(5,267.066)	(176.972)	(170.582)
Observations	332	326	311	305
Regional fixed effect	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y
R-squared	0.69	0.72	0.50	0.52

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

	A jack-knifed regional average of ECI		A jack-knifed regional average for ECI and Income	
	(1)	(2)	(3)	(4)
Variables	COVID-19 cases	COVID-19 death	COVID-19 cases	COVID-19 death
A. Second-stage estimates. Dependent variables are COVID-19 cases and COVID-19 deaths respectively				
ECI	**-718.23*** **	**-12.32** **	**-730.80*** **	**-12.50** **
	(115.109)	**(5.207)**	**(115.339)**	**(5.172)**
B. First-stage estimates. Dependent variable is ECI				
IV	-21.872***	-21.73 ***	-21.95 ***	-21.82***
	(0.769)	(0.809)	(0.771)	(0.813)
Baseline controls	Y	Y	Y	Y
Regional fixed effects	Y	Y	Y	Y
Cluster robust standard	Y	Y	Y	Y
Observations	326	305	326	305
Centered R2	0.72	0.51	0.72	0.51
F-test	44.34	40.40	41.15	37.52
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) statistic)	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: (1) 16.38 (10% maximal IV size), 8.96 (15% maximal IV size), 6.66(20% maximal IV size), 5.53 (25%) maximal IV size)s 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), 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. OLS regression analysis results to investigate the association between ECI and some public health outcomes in UK local authorities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Mortality rate-Cardiovascular	Mortality rate Cancer	Cancer rate	Diabetes rate	Physical activity rate	Smoking rate at delivery	Life expectancy
ECI	**-2.25****	**-0.46**	**0.04**	**-4.10*****	**1.75*****	**-0.96*****	**-0.14**
	(1.036)	**(1.008)**	**(0.384)**	**(0.819)**	**(0.465)**	**(0.221)**	**(0.124)**
IMD index	218.54***	282.27***	-32.15***	10.39	-45.54***	43.74***	-15.78***
	(19.287)	(16.193)	(8.159)	(14.551)	(7.958)	(5.880)	(1.861)
Cost of Housing	0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Population density	-0.00	-0.00	0.00**	0.00	-0.00	-0.00**	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ethnic groups	-0.02	-0.54***	0.01	0.07	-0.14***	-0.11***	0.01
	(0.087)	(0.080)	(0.034)	(0.069)	(0.043)	(0.015)	(0.010)
Percentage of people working in risky jobs	0.36***	0.29***	0.02	0.28***	-0.19***	0.04	-0.01
	(0.131)	(0.105)	(0.046)	(0.088)	(0.050)	(0.032)	(0.014)
Percentage of adults with obesity	-0.17**	-0.18***	-0.01	-0.05	0.07**	-0.00	0.02
	(0.080)	(0.058)	(0.032)	(0.048)	(0.030)	(0.012)	(0.014)
Median age	-0.69***	-1.60***	-0.05	-0.50***	0.15*	-0.01	
	(0.171)	(0.181)	(0.068)	(0.145)	(0.090)	(0.046)	
Male population	94.75	-66.38	-17.72	3.12	37.46		-6.24

	(67.562)	(74.413)	(30.528)	(55.460)	(35.370)		(6.445)
Constant	25.53	207.63***	69.10***	91.74***	50.25***	6.99***	84.05***
	(36.675)	(39.780)	(15.568)	(29.466)	(19.259)	(2.566)	(3.262)
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	0.84	0.84	0.30	0.43	0.58	0.75	0.65

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.

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