An annual deprivation index for neighbourhoods in England

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Abstract

Deprivation can be defined as a state of exclusion from the ordinary customs and activities of society. Much activity is devoted to the relief or reduction of deprivation, as well as its measurement. However, there is no annual measure of deprivation in England, nor a measure which allows changes in deprivation to be tracked over time. In fact, the flagship measure – the Index of Multiple Deprivation – is an ordinal measure that has only been updated five times since its original release at the turn of the millennium. In this paper, we solve these problems by presenting a new Annual Deprivation Index. This new index is compiled from a smaller number of data sources than the Index of Multiple Deprivation, which allows it to be updated on an ongoing basis, providing policy-making institutions with timely access to contemporary information on deprivation. The higher-frequency, lower-complexity nature of the Annual Deprivation Index makes it a natural complement to the Index of Multiple Deprivation. Moreover, the fact that our new index is cardinal means that it captures changes in deprivation over time, and avoids some well-known issues with ordinal indices. To illustrate its application, we use our new index to measure the changing incidence of deprivation during the Covid-19 pandemic, and to analyse local authorities assigned to a recent post-Covid place-based policy.

Keywords: Deprivation, social indicators, social policy, health, unemployment, crime.

JEL Codes: C43, H55, I18, I30, I32.

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1 Introduction

Deprivation, as conventionally defined, is a lack of access to the basic standards of consumption, working conditions, and social activities which are expected or considered necessary. In other words, it is a state of exclusion from the ordinary customs and activities of society (Townsend, 1979). Much government and third sector activity is devoted to the relief or reduction of deprivation, and various attempts to measure it have been developed to support these activities. In Britain, the English, Scottish and Welsh Indices of Multiple Deprivation are the most well-known approaches. The first English index was introduced by the Office of the Deputy Prime Minister in 2000, while the most recent version was released by the Ministry of Housing, Communities and Local Government in 2019.

The Indices of Multiple Deprivation are used by central and local government to inform a variety of policy decisions. For example, early releases were used to identify the local authorities eligible for New Labour's Neighbourhood Renewal Fund (Deas et al., 2003). More recently, the 2019 release of the English index (henceforth, IMD) has been used by the Conservative government to allocate local authorities to its High Streets Task Force (HM Government, 2022, pp. 211). Outside of government, the IMD is regularly used by third sector organisations to identify deprived areas and access funding, and by academics to study the causes and consequences of deprivation. It is regularly quoted by journalists and thinktanks in policy-related discussion.

The IMD is based on seven 'domains' (or types) of deprivation: income deprivation; employment deprivation; education, skills, and training deprivation; health deprivation and disability; crime; barriers to housing and services; and living environment deprivation. In turn, each of these domains is constructed from a large number of underlying indicators. For example, the health and disability domain is computed using data on mortality, morbidity, comparative illness and disability, and mood and anxiety disorders. Given the sheer volume of data required to compute these domains, the IMD has only been updated five times since its original release at the turn of the millennium. And because not all of the underlying data are released annually, lagged data are used in many cases. Of the 39 indicators used to compute the 2019 IMD, for example, only a small number were published in 2019. The majority were published between 2015 and 2017, with some domains using information from 2008 (McLennan et al., 2019, appendix A).

Different types of policy require different types of information. Some policy design problems require detailed measures of slow-moving types of deprivation, for which the IMD is well-suited. But many policy decisions require more timely, higher frequency indicators of deprivation than the IMD can provide. For example, the Covid-19 pandemic and associated lockdowns had a significant effect on UK high streets, with footfall halving between 2019 and 2020 (Enoch et al., 2022). Despite this, the local authorities allocated to the Conservative government's High Streets Task Force were determined using the 2019 IMD, in which the majority of indicators date from 2017 or earlier. It is not clear that the local authorities allocated to the High Streets Task Force on this basis will be those most in need of support.

In this paper we present an Annual Deprivation Index for neighbourhoods in England. As its name suggests, the Annual Deprivation Index, henceforth ADI, is an annual-frequency index that will be updated every year to provide policy-making institutions with timely access to contemporary information on deprivation. To achieve this, the ADI is designed to be a lower-complexity index than the IMD, in the sense that it uses fewer domains of deprivation, and therefore fewer underlying indicators. In this sense, the ADI is a natural complement to the IMD in the measurement of deprivation in England. At the same time, the ADI presents some statistical advantage over the IMD, as it is a cardinal measure which can be used to measure the extent to which deprivation has increased or decreased over time. This also allows the ADI to avoid rank reversal issues that affect the IMD.

We first provide a brief description of the IMD, followed by a description of our new index. We then compare the rankings generated by our index with those generated by the IMD. We show that the adoption of a cardinal deprivation measure avoids the issue of rank reversal, and connect this to Arrow's Impossibility Theorem. Finally, we use our index to measure the changing incidence of deprivation around the Covid-19 pandemic, and examine the local authorities assigned to the High Streets Task Force.

2 The Index of Multiple Deprivation

The English IMD uses lower-level super output areas as its unit of observation, which are small neighbourhoods with approximately 1500 inhabitants on average. The index is based on seven domains of deprivation: income deprivation; employment deprivation; education, skills, and training deprivation; health deprivation and disability; crime; barriers to housing and services; and living environment deprivation. This approach acknowledges the multi-dimensional nature of deprivation, defined as the exclusion from a set of social needs (Rawls, 1971; Townsend, 1979, 1987), and its difference to poverty, which can be defined as a lack of the financial resources necessary to meet these needs (Noble et al., 2006).

The IMD is constructed by first calculating domain scores and then aggregating over these scores using a fairly complex transformation and ranking algorithm. A domain score is calculated for each neighbourhood in England and each domain of deprivation. Denote a score for domain j in neighbourhood i by z_{ij}. These scores are computed using the indicators listed in table 1, and are generally weighted averages. The domain scores are then ranked such that r_{ij} is the position of neighbourhood i in the set of all English neighbourhoods ranked by domain score j. Normalised domain ranks $R_{ij} \in (0, 1]$ are then computed, where $R_{ij} = 1$ for the neighbourhood with the highest domain score. These normalised domain ranks are transformed to produce transformed domain scores as follows,

$$X_{ij} = -23 \ln\left(1 - R_{ij}\left(1 - e^{-\frac{100}{23}}\right)\right), \tag{1}$$

such that the transformed domain scores $X_{ij} \in (0, 100]$ have an approximately exponential distribution. The purpose of this transformation is to 'amplify' those domain ranks which indicate a high level of deprivation for a particular domain. This prevents a high rank in one or more domains being offset by low ranks in other domains. The scaling parameter in (1) is equal to 23, which ensures that approximately 10% of the lower-level super output areas fall within the top half of the distribution and 90% in the bottom half.

The IMD score for each neighbourhood is constructed as a weighted average of the domain scores,

$$\text{IMD}_i = \sum_{j=1}^{7} \omega_j X_{ij}, \tag{2}$$

where the weights ω_j are given in the first column of table 1. We can therefore summarise

Table 1: IMD 2019 domains and indicators

Sub-index (domain)	Indicators entering sub-index
Income (22.5%):	Income support families,
	Income-based Jobseeker's Allowance families,
	Income-based Employment and Support Allowance families,
	Pension Credit (Guarantee) families,
	Child Tax Credit and Working Tax Credit families, below 60% median income and not counted above,
	Asylum seekers in England in receipt of subsistence support, accommodation support, or both,
	Universal Credit families where no adult is in the "Working - no requirement" regime.
Employment (22.5%):	Adult claimants of Jobseeker's Allowance,
	Adult claimants of Employment and Support Allowance,
	Adult claimants of Incapacity Benefit,
	Adult claimants of Severe Disablement Allowance,
	Adult claimants of Carer's Allowance,
	Adult claimants of Universal Credit in the "Searching for work" and "No work requirements" regimes.
Education (13.5%):	Key stage 2 attainment: average points score,
	Key stage 4 attainment: average points score,
	Secondary school absence rate,
	Students staying on in education post 16,
	Students entering higher education,
	Adults with no or low qualifications,
	Adult English language proficiency.
Health and disability (13.5%):	Years of potential life lost,
	Comparative illness and disability ratio,
	Acute morbidity,
	Mood and anxiety disorders.
Housing and services (9.3%):	Road distance to post office, primary school, general store or supermarket, GP surgery,
	Household overcrowding,
	Homelessness,
	Housing affordability.
Crime (9.3%):	Crime rates for violence, burglary, theft and criminal damage.
Living environment (9.3%):	Housing in poor condition,
	Houses without central heating,
	Air quality,
	Road traffic accidents.

Notes: See McLennan et al. (2019) for more details, particularly figure 3.2. The domain weights ω_j in (2) are given in brackets in the first column. The indicators in the 2015 index, described in Smith et al. (2015b), are very similar, and the domain weights are identical.

the IMD score for neighbourhood i as,

$$\text{IMD}_i = \sum_{j=1}^{7} \omega_j f(r_{ij}), \tag{3}$$

i.e., as a weighted average of transformed domain ranks.

Finally, the IMD scores are ranked and the rank for each neighbourhood is reported as an ordinal variable. Detailed descriptions of the IMD, including a rationale for the transform in (1), can be found in Smith et al. (2015a,b) and McLennan et al. (2019).

As noted above, the complexity of the IMD means that it has only been produced about three times per decade, using data sources from multiple years. In fact, the 2019 index uses 39 indicators, with the majority relating to data from 2015, 2016 and 2017. The employment deprivation domain, for example, uses data from 2015 and 2016 on Jobseeker's Allowance, Employment and Support allowance, Incapacity Benefit, Severe Disablement Allowance, Carer's Allowance, and Universal Credit (McLennan et al., 2019, appendix A). These lags may not cause problems when the extent and geographical incidence of deprivation are stable, but policy decisions may require more contemporaneous data when deprivation is changing rapidly. As noted above, allocating local authorities to the Conservative government's High Streets Task Force is an example of this type of decision. In the next section, we describe an Annual Deprivation Index based on contemporaneous data.

3 The Annual Deprivation Index

Deprivation is inherently multi-dimensional, and any deprivation index will necessarily incorporate information from multiple sources. The IMD, discussed above, uses information on seven domains of deprivation, but this limits the frequency at which the index can be produced. Moreover, much of the information in the IMD is out of date by the time it is published. These two observations suggest that a deprivation index that uses fewer domains, and therefore achieves a higher and more contemporaneous release frequency, could act as a useful complement to the IMD in the measurement of deprivation in England. This is exactly what our Annual Deprivation Index is designed to achieve.

The ADI uses the same geographical unit of observation as the IMD: lower-level super output areas. Unlike the IMD, which uses seven domains of deprivation, the ADI uses three: employment, crime, and health. Scores for each of these domains are calculated annually for each LSOA, with a primary indicator being selected for each. For employment, the domain score is the number of individuals claiming benefits principally for the reason of being unemployed.[1] For crime, the domain score is the sum of criminal offences in the relevant year.[2] And for health, the domain score is the sum of registered cases of depression and other mental health illnesses.[3].

[1]This is the sum of the number of people claiming Jobseeker's Allowance plus those who claim Universal Credit and are required to seek work and be available for work. These data can be acquired from NOMIS at https://www.nomisweb.co.uk/.

[2]In turn, these can be broken down into anti-social behaviour offences, bicycle thefts, burglaries, criminal damage and arson offences, drug offences, theft, possession of weapons, public order offences, robbery, shoplifting, vehicle crime, and violence and sexual offences. These data can be acquired from the open data site for crime and policing at https://data.police.uk/data/archive/.

[3]These data can be acquired from the Quality and Outcomes Framework dataset available at https:

The employment, crime and health domains were chosen by a simple method. Essentially, they are the subset of domains in the IMD for which publicly available annual data are released in a timely fashion, and for which commensurable cardinal measures are available. The IMD suggests that, aside from the employment, crime and health domains that we include in the ADI, information on education and the living environment should also be included in a full measure of deprivation. Similar approaches to deprivation, such as the Bristol Social Exclusion Matrix, also suggests that civic, cultural and political participation should be included (Levitas et al., 2007). However, the available indicators for these domains are either not available at annual frequency, or not available in a form that is commensurable with the employment, crime and health indicators. For example, while 'persons affected by crime' and 'persons affected by ill health' are at least potentially commensurable, IMD indicators like 'average key stage 2 attainment scores', 'road to distance to a post office' or 'houses without central heating' are incommensurable with both themselves and with the employment, crime and health indicators.

Thus, while the three domains in the ADI capture a subset of the different dimensions of deprivation proposed by the IMD, they have two important features in common: they have information available at annual frequency, and they are commensurable with one another. In other words, they can be measured in a timely fashion, and each social security claim, criminal offence or illness indicates that one or more persons is experiencing deprivation of some form. Using the language of (Levitas et al., 2007), our social security claims indicator is a direct measure of economic exclusion, while our crime and health indicators capture two different dimensions of quality-of-life exclusion, and these different 'deprivation cases' can be summed to give a cardinal measure of deprivation in each neighbourhood.

If A_{ie} denotes the number of deprivation cases in the employment domain in neighbourhood i, A_{ic} denotes the number of deprivation cases in the crime domain in neighbourhood i, A_{ih} denotes the number of deprivation cases in the health domain in neighbourhood i, and P_i denotes the total population of neighbourhood i, then the ADI score for neighbourhood i is the total number of deprivation cases normalised by population:

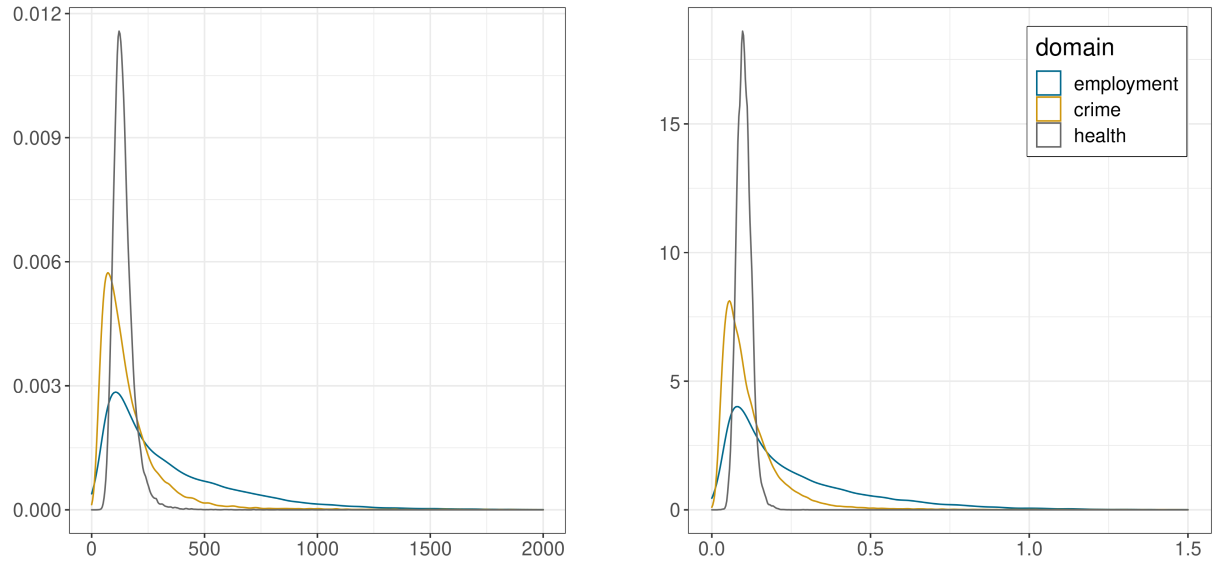
$$\mathrm{ADI}_i = \frac{A_{ie} + A_{ic} + A_{ih}}{P_i}. \tag{4}$$

As we include all of the domain and population data with the ADI, users can recover an un-normalised deprivation count if they wish. Unlike the ordinal IMD score in (3), the ADI score in (4) is a meaningful cardinal measure. Neighbourhoods can of course be ranked to permit comparison with the IMD.

Thus, unlike the IMD, the overall ADI score for each LSOA is not a normalised sum of domain ranks, transformed or otherwise. Instead, it is simply the sum of three commensurable types of deprivation cases, normalised by total population. Importantly, as shown in figure 1, the distributions of deprivation cases over LSOAs are similar for each of the three domains, indicating that the ADI score is not completely dominated by a single domain.

The full ADI dataset, which includes all of the relevant domain information, including the separate types of crime counts and further information on mental health and non-mental

//digital.nhs.uk/data-and-information/publications/statistical/quality-and-outcomes-framework-achievement-prevalence-and-exceptions-data. Unlike the claimant count and crime data, these data are only available for GP surgery catchment areas. The process by which we estimate cases for lower-level super output areas is described in appendix B.



(a) Density of A_{id} for $d \in \{e, c, h\}$.

(b) Density of A_{id}/P_i for $d \in \{e, c, h\}$.

Figure 1: Kernel density estimates of deprivation cases across lower-lower super output areas, un-normalised and normalised, for each of the three deprivation domains in the ADI. For definitions, see the discussion in section 3.

health illnesses, can be accessed at https://annualdeprivationindex.co.uk/. A description of the health data included in the full dataset can be found in appendix A. Finally, it is important to mention that the ADI data are presented as they are downloaded from publicly available sources. Unlike the IMD, therefore, we do not apply shrinkage methods before release (or utilise any non-publicly available information). This is to ensure replicability by third parties, but it does mean that some measurement error will exist in the data.

To flag potential measurement errors for users, we also include residuals from neighbourhood-by-neighbourhood time series regressions studentised by cross-sectional distribution. Specifically, if A_{idt}/P_{it} is the normalised number of deprivation cases in domain $d \in \{e, c, h\}$ in neighbourhood $i = 1, ..., N$ at time $t = 1, ..., T$, then $\hat{u}_{idt}$ is the residual from the regression of $\ln(A_{idt}/P_{it})$ on time, i.e.,

$$\ln\left(\frac{A_{idt}}{P_{it}}\right) = \alpha_{id} + \beta_{id}t + u_{idt}. \tag{5}$$

We then studentise the set of residuals in each year by their cross-sectional standard deviation, i.e,

$$z_{idt} = \frac{\hat{u}_{idt}}{\sqrt{\sum_{i=1}^{N}(\hat{u}_{idt} - \bar{u}_{dt})^2/N}}, \tag{6}$$

in which $\bar{u}_{dt} = \sum_{i=1}^{N} \hat{u}_{idt}/N$ is the cross-sectional sample mean of the residuals in year t. Any observation in which $\text{abs}(z_{idt}) > 3$ can be used as an indicator that the data point in question is unusually far from its time trend compared to data points within the same year, suggesting that care (and further investigation) should be taken before using these observations for estimation, inference, or policy assignment.

4 Comparison of the ADI and IMD

4.1 Statistical correlation

As discussed in the preceding sections, the ADI uses a lower number of higher frequency indicators than the IMD, thus sacrificing domain complexity to gain a higher sample frequency. In this section we consider the implications of this trade-off by investigating the extent to which the ADI captures the same information as the IMD in those years in which the latter is available, as well as the extent to which the ADI varies between years. The former gives an indication of how much information is lost by reducing domain complexity; the latter provides an indication of how much is gained by increasing frequency.

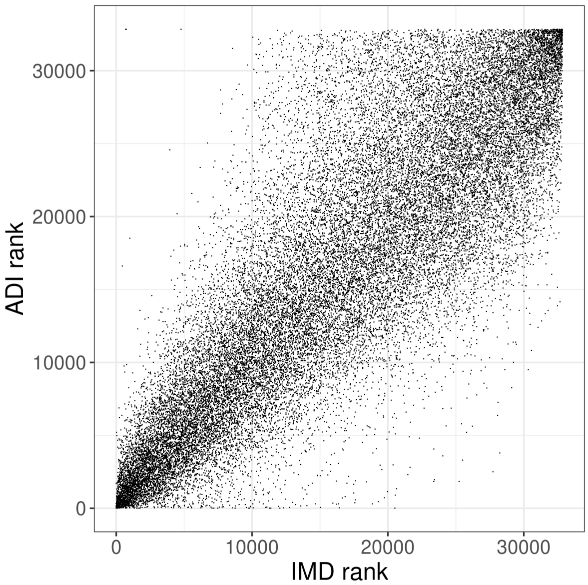
The current iteration of the ADI covers the years 2013 to 2020 inclusive. This range includes two years, 2015 and 2019, for which the IMD was released. As illustrated in the top two panels of figure 2, the ADI captures very similar information to the IMD in both 2015 and 2019, the two years in which the indices overlap. Kendall's rank correlation between the two indices is 0.67 in 2015 and 0.68 in 2019, implying that 83% of the potential comparisons in 2015 are concordant, and 84% in 2019.[4] This indicates a relatively strong overlap between the two indices; as discussed in Calvert Jump & Michell (2020), a Kendall's rank correlation above 0.5 can be considered a 'strong' correlation.

We provide further analysis of the cross-sectional informational overlap between the ADI and IMD for coincident years in appendix C. The most notable conclusion is that neighbourhoods in some rural peripheries, e.g., rural Cornwall or coastal Lincolnshire, are found to be more deprived when using the IMD, but less deprived when using the ADI. This is not particularly surprising, as the ADI does not utilise certain measures of living environment deprivation (e.g., average distances from post offices) which are more pronounced in rural areas. But this is exactly the type of slow-moving deprivation that the IMD is naturally more suited to measuring. Moreover, when deprivation is summarised at the more policy-relevant level of local authorities, the two indices are highly correlated. We use the ADI to provide an analysis of the local authorities assigned to the High Streets Task Force in this appendix.

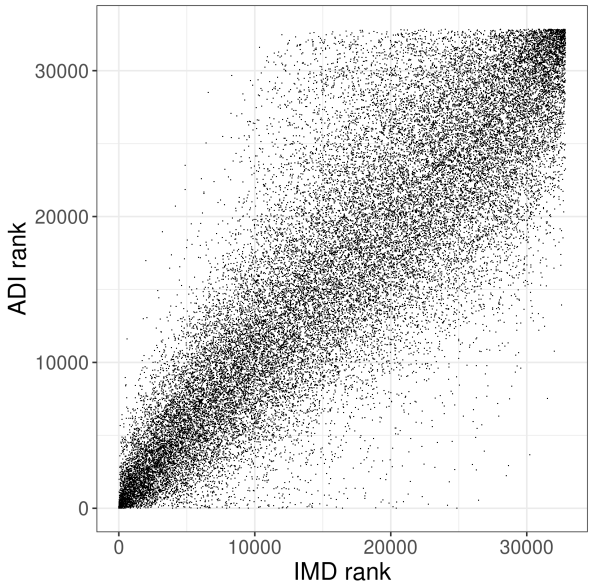
The lower panel of figure 2 plots Pearson's correlation coefficient with 99% confidence intervals for the ADI in each year between 2015 and 2020 and the preceding year. While the geographical incidence of deprivation is very stable in the years preceding the Covid-19 epidemic, there is an obvious change in the geography of deprivation between 2019 and 2020, as a result of the epidemic. We explore these changes in section 5, below.

Thus, the ADI has a very high rank correlation with the IMD for the years in which the latter is released, suggesting that limited information is sacrificed by reducing the number of domains. Over time, deprivation rankings are relatively stable until the pandemic, which generates significant inter-year variation in the ADI. This suggests the potential for considerable information loss at the lower frequency of the IMD. In combination, these results suggest that a deprivation index at a point on the tradeoff between frequency and complexity which targets a more frequent release date at the expense of fewer domains of deprivation is a useful complement to the IMD.

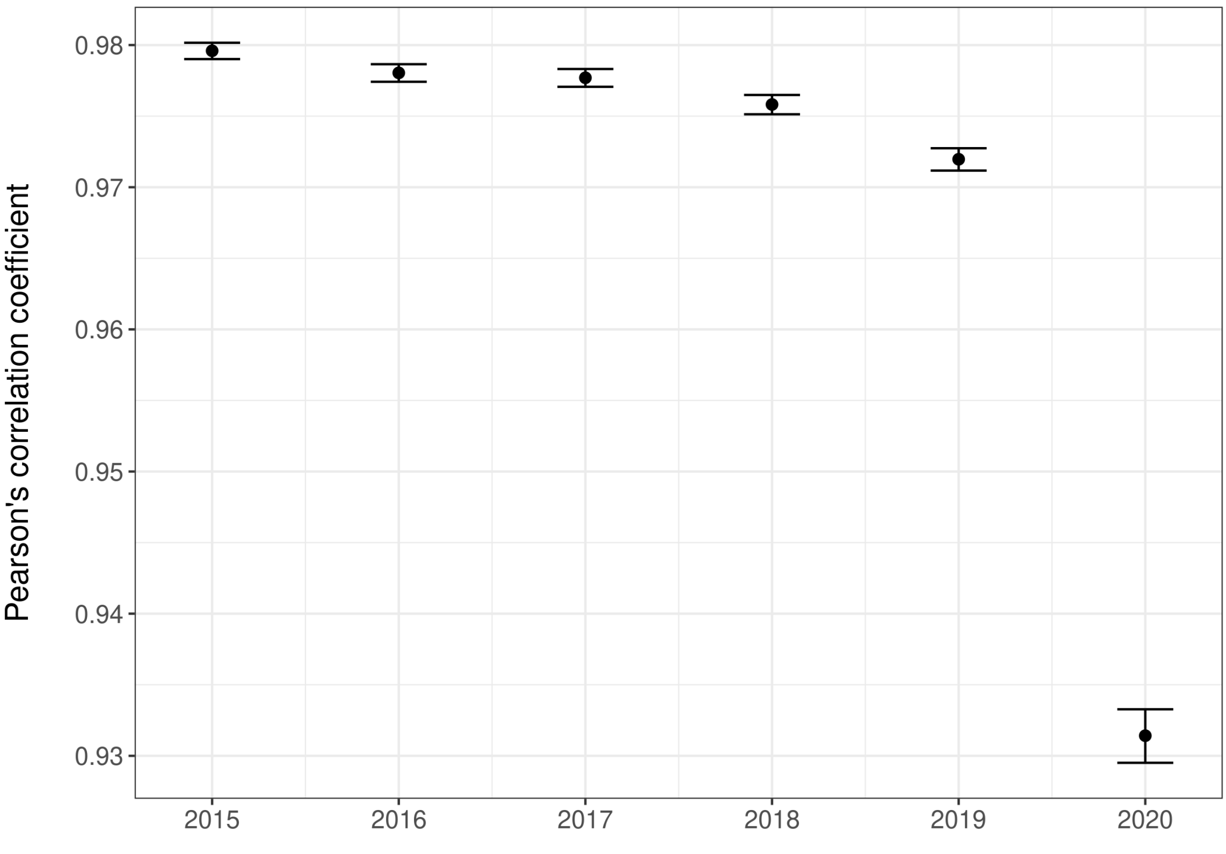
[4]If $(\mathrm{ADI}_i, \mathrm{IMD}_i)$ and $(\mathrm{ADI}_k, \mathrm{IMD}_k)$ are observations from neighbourhoods i and k, they are said to be concordant if $\mathrm{sgn}(\mathrm{ADI}_i - \mathrm{ADI}_k) = \mathrm{sgn}(\mathrm{IMD}_i - \mathrm{IMD}_k)$, and discordant otherwise. Kendall's tau can be interpreted as the probability that a randomly chosen pair is concordant minus the probability that it is discordant, thus $\tau \in [-1, 1]$, as with the Pearson correlation coefficient.



(a) Rank-rank plot of IMD and ADI in 2015.



(b) Rank-rank plot of IMD and ADI in 2019.



(c) Time series plot of Pearson's correlation between ADI in year t and $t-1$, with 99% confidence intervals.

Figure 2: Correlation between the ADI and IMD, and inter-year correlation structure of the ADI. For definitions, see section 4.

4.2 Rank reversal in ordinal indices

The relatively straightforward compilation method used for the ADI means that it has a cardinal interpretation, unlike the IMD. This is useful in itself, because it means that the ADI can be used to determine whether a neighbourhood has become more or less deprived over time in isolation of comparator neighbourhoods. This is not possible with the IMD, because the IMD only tells us whether the position of a neighbourhood has changed relative to other neighbourhoods.

The cardinal construction method of the ADI also solves an important statistical problem with the IMD, that of rank reversal. In the case of geographical deprivation, rank reversal refers to the problem that deprivation rankings depend not only on those neighbourhoods included as comparators, but also those neighbourhoods *not* included. When using the IMD, which of two neighbourhoods is ranked are more deprived depends on which *other neighbourhoods* they are compared to. Adding or removing comparators can cause rankings to 'flip', or reverse.

Formally, rank reversal in a social indicator is defined as follows:

> If i is ranked above k in the set of alternatives $\{i, k\}$, a *rank reversal* occurs if k is ranked above i in the set of alternatives $\{i, k, l\}$.

See e.g., Wang & Luo (2009). Suppose we find that neighbourhood i is more deprived than neighbourhood k when we calculate the IMD using information from neighbourhoods i and k only. A rank reversal occurs if we find that neighbourhood k is more deprived than neighbourhood i when we calculate the IMD using information from neighbourhoods i, k and l.

There appears to be little discussion of rank reversal in the context of the IMD. However, rank reversal is an intuitively undesirable characteristic of composite indicators in general, as acknowledged by the OECD (OECD, 2008). From a policy perspective, rank reversal implies the possibility that a neighbourhood might be eligible for a policy when compared with neighbourhoods across the whole of England, but cease to be eligible when compared with neighbourhoods in its locality. In general, rank reversal is an irrational attribute of a poverty or deprivation index, as the example in table 2 makes clear.

In this example, we first calculate the IMD ranks for Birmingham 046A and 046C using only the domain scores for these two neighbourhoods. This generates the result that that Birmingham 046C is more deprived than Birmingham 046A. We then add a third neighbourhood in East Hertfordshire to the calculation, and re-compute the ranks. With the third neighbourhood included, we find that Birmingham 046A is more deprived than Birmingham 046C; a rank reversal has occurred.[5]

Rank reversal is closely related to the independence of irrelevant alternatives axiom in social choice theory, which in the present context can be defined as follows:

> A deprivation index respects *independence of irrelevant alternatives* if the relative ranking of two neighbourhoods depends only on their relative ranking in each domain.

[5] In this example we calculate the normalised domain ranks R_{ij} by dividing through by the maximum rank, but the result is robust to various normalisation procedures.

This way of stating the axiom follows Geanakoplos (2005), and it follows that the IMD in (1) - (3) does not satisfy the axiom, as the IMD scores are weighted averages of transformed ranks. As such, the difference in IMD scores between two neighbourhoods depends on the magnitude of the differences between their ranks over the seven domains, and thus (implicitly) the position of other 'irrelevant' neighbourhoods in the domain rankings.

In fact, it follows from Arrow's impossibility theorem that any aggregation of ordinal domain ranks cannot resolve the rank reversal problem while simultaneously satisfying the following attributes:

1. *Unrestricted Domain*, i.e., any combination of domain ranks can be used to compute the deprivation index;
2. *Unanimity*, i.e., the deprivation index ranks neighbourhood i above neighbourhood k whenever every domain ranks i above k;
3. *Non-dictatorship*, i.e., the deprivation index is not based entirely on a single domain;
4. *Complete Ordering*, i.e., the index provides an unambiguous ranking between every pair of neighbourhoods.

See e.g., Morreau (2016) or Weymark (2016). The fact that deprivation indices are calculated using empirical data makes it operationally difficult to abandon attribute 1. Attribute 2 is intuitively necessary for any meaningful deprivation index, and it is similarly difficult to abandon attribute 3 given the multi-dimensional nature of deprivation. Attribute 4, on the other hand, is intuitively possible to abandon, but might prove problematic when assigning areas to policies.

The obvious solution to rank reversal, therefore, is to abandon the computation of a multi-dimensional deprivation index by the aggregation of ordinal domain ranks. This is exactly the approach taken by the ADI, which is a normalised sum of deprivation cases over different domains, and thus a cardinal measure of deprivation. Clearly, given (4), the ADI score for any neighbourhood i uses information from that neighbourhood only, and therefore rank reversal cannot occur. Thus, as well as including much the same information as the IMD for those years in which the latter exists, and being available at annual frequency, the ADI also solves a key statistical problem with the IMD.

Table 2: An example of rank reversal in the IMD.

Calculating IMD ranks using two neighbourhoods:

Neighbourhood	Domain scores	IMD score	IMD rank
Birmingham 046A	$\{0.26, 0.184, 57.0, 1.17, 0.74, 27.0, 35.8\}$	57.4	1
Birmingham 046C	$\{0.27, 0.181, 42.5, 1.11, 0.89, 34.5, 37.0\}$	58.2	2

Calculating IMD ranks using three neighbourhoods:

Neighbourhood	Domain scores	IMD score	IMD rank
Birmingham 046A	$\{0.26, 0.184, 57.0, 1.17, 0.74, 27.0, 35.8\}$	59.1	3
Birmingham 046C	$\{0.27, 0.181, 42.5, 1.11, 0.89, 34.5, 37.0\}$	48.7	2
East Hertfordshire 002B	$\{0.06, 0.037, 10.2, \text{-}1.9, \text{-}0.24, 45.4, 51.3\}$	26.1	1

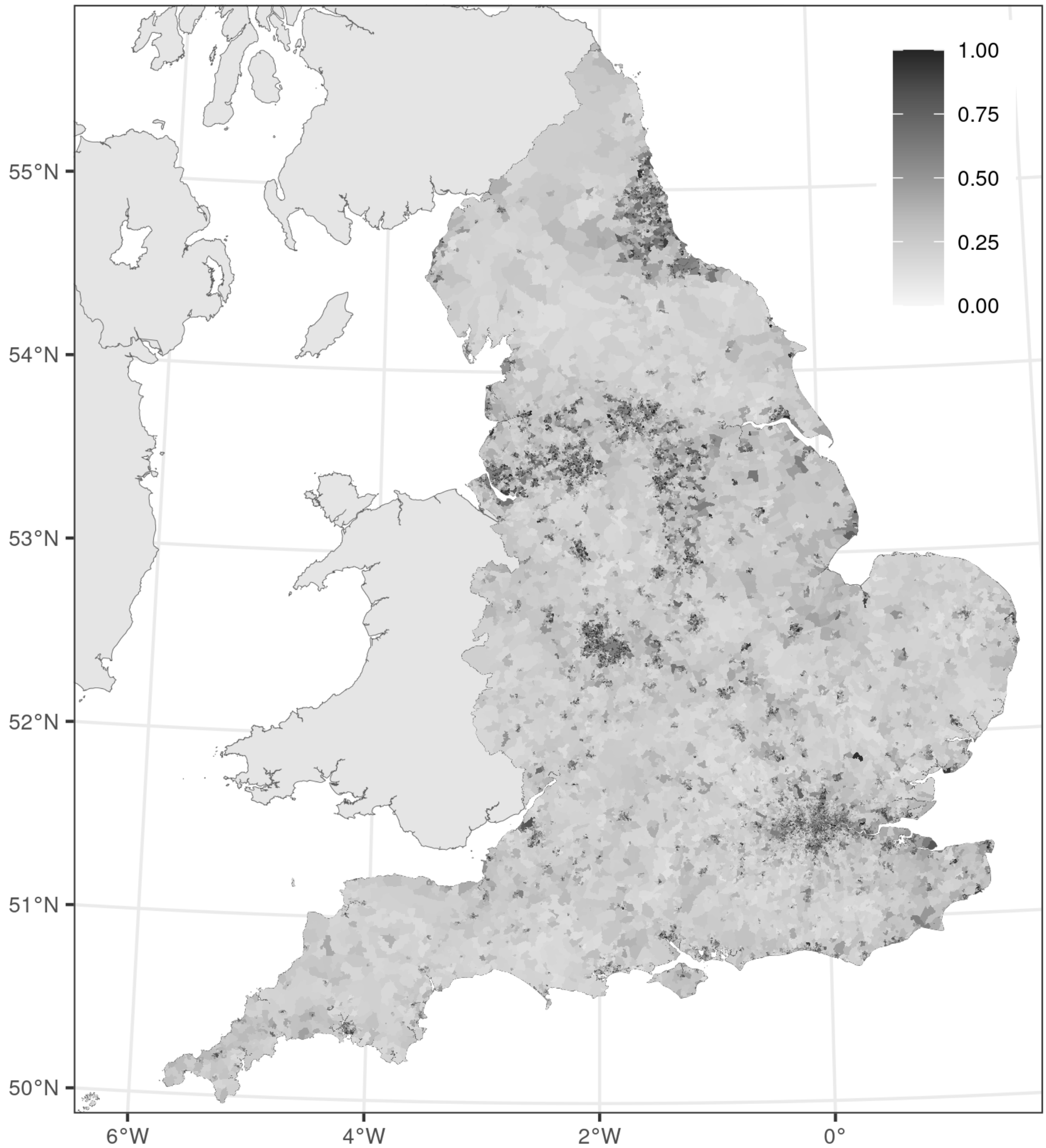


Figure 3: Normalised ADI choropleth, 2019 data.

5 The impact of Covid-19 on deprivation in England

In this section, we use the ADI to examine the extent to which deprivation was affected by the Covid-19 pandemic. Figure 3 presents a choropleth mapping the extent of deprivation across English neighbourhoods in 2019 (built using `ggplot`, see Wickham, 2016). We can see that severe deprivation, measured by the normalised ADI index, was mainly concentrated in and around major cities in 2019, with other well-known pockets of deprivation observable around the coastal periphery and South Yorkshire.

Figure 4 presents a choropleth mapping the extent of deprivation in 2020, after the first wave of the Covid-19 epidemic. It is clear from comparing figures 3 and 4 that deprivation cases increased significantly across all parts of the country. However, it is also obvious that this change was not felt equally. While the more affluent parts of England were affected,

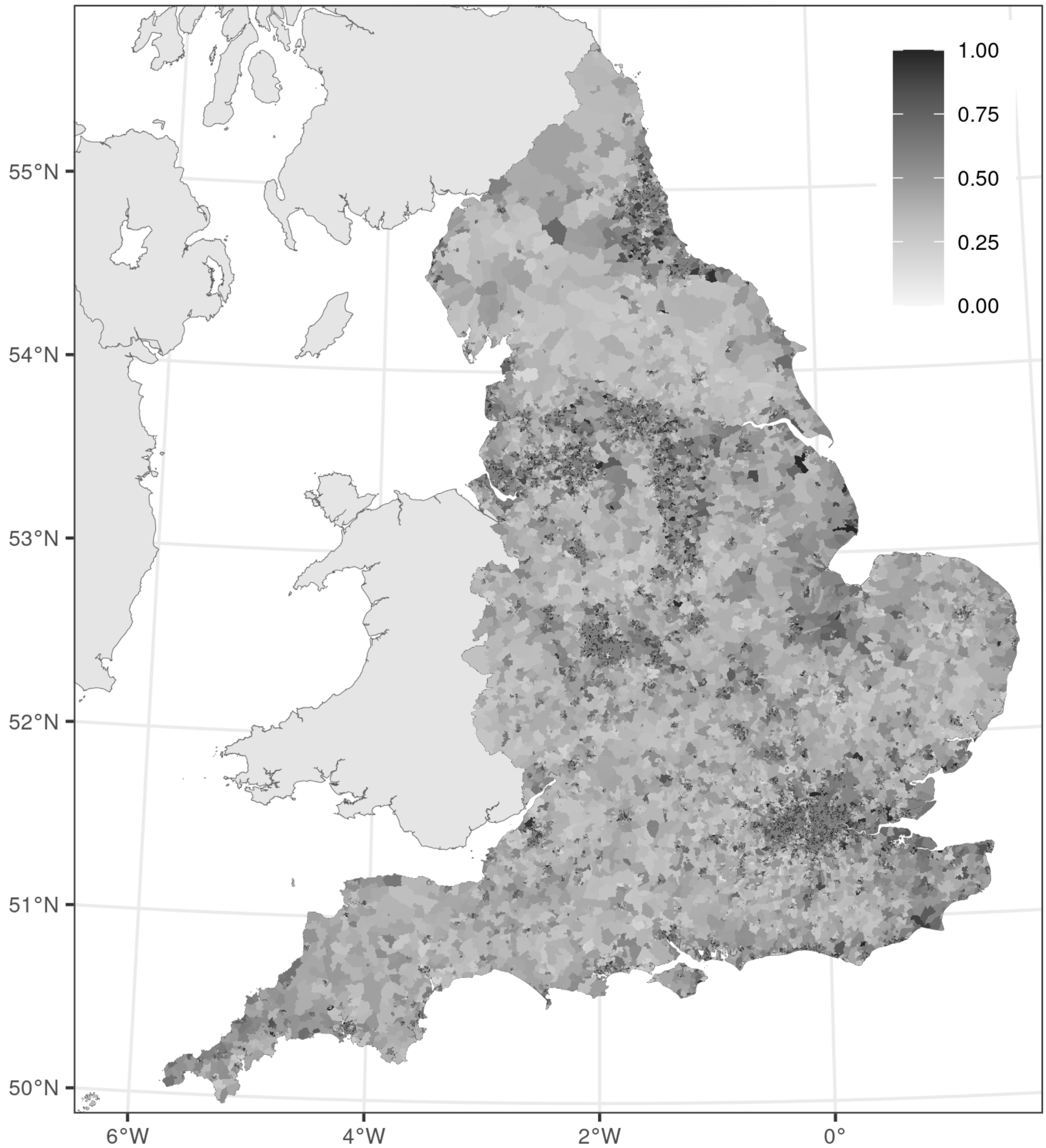


Figure 4: Normalised ADI choropleth, 2020 data.

cities and the coastal periphery were hit the hardest. This is particularly true of regions like Cornwall and those parts of the East Coast which have struggled economically since the 1980s. This impression is reinforced by figure 5, which maps the change in the normalised ADI index between 2019 and 2020. The increases in deprivation cases in those parts of Cornwall, Kent, and Lincolnshire which have been historically associated with deprivation and relative decline are very obvious here.

Thus, the impact of the Covid-19 epidemic on deprivation in England seems to have largely followed the same pattern of deprivation that has existed in England since (at least) the heyday of regional policy in the 1960s. The effects of Covid-19 on deprivation in England are thus not 'special' in any great sense: the inner cities and peripheral regions have borne the brunt of it. This observation complements the well-known fact that people who live in the most deprived areas of England had a considerably higher risk of dying after contracting

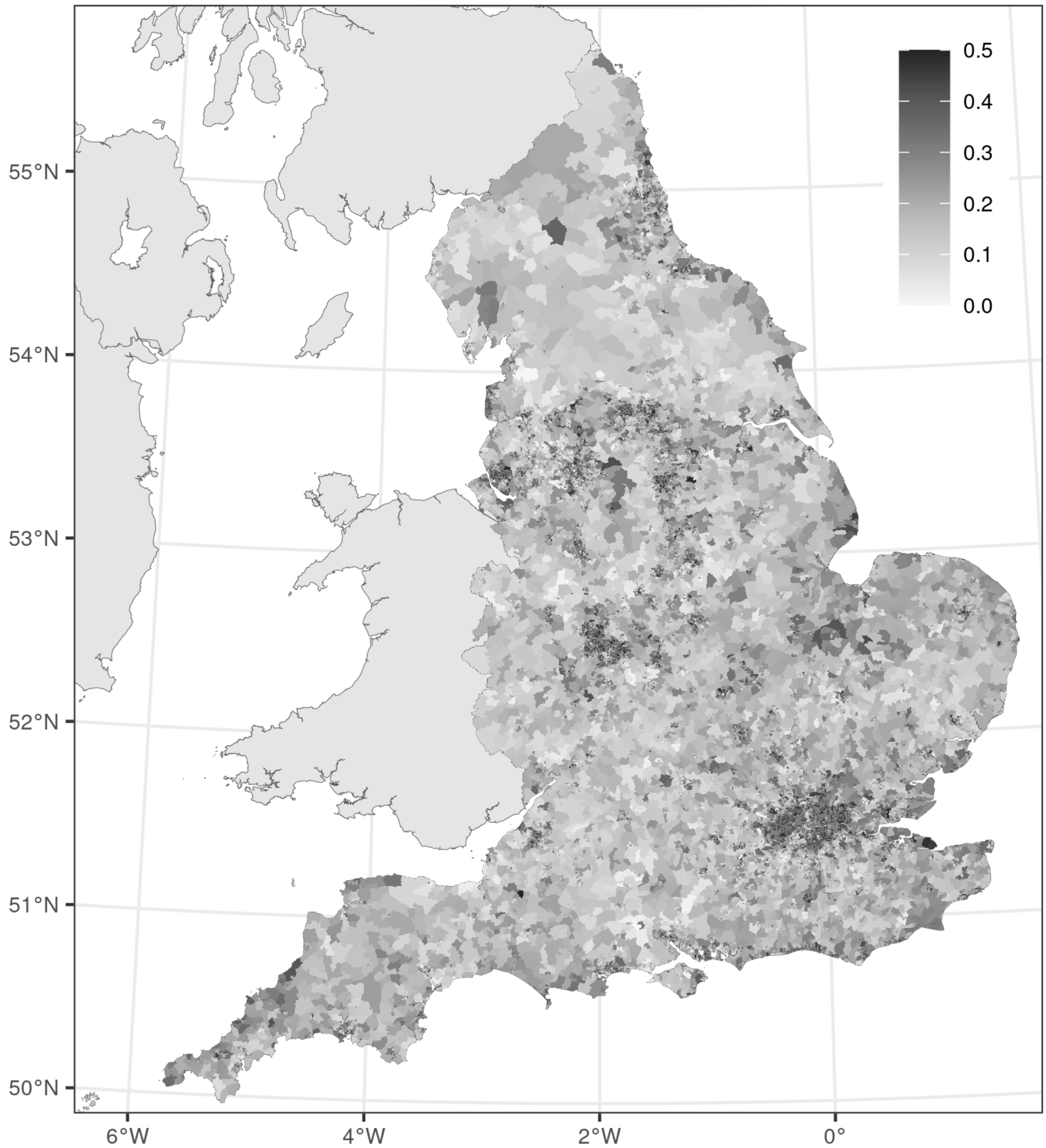


Figure 5: Change in normalised ADI between 2019 and 2020.

Covid-19 (see, e.g., O'Dowd, 2020). The most deprived parts of England were, therefore, the most affected by both the direct and indirect effects of the pandemic.

Finally, as illustrated in figure 6, the changes in deprivation cases observed between 2019 and 2020 have largely been driven by changes in joblessness. On average, health and crime deprivation cases did not change signficantly between 2019 and 2020, although some areas saw increases while some areas saw decreases. The vast majority of neighbourhoods, however, saw increases in social security claims related to joblessness, despite the introduction of furlough and the self-employment income support scheme. This observation provides prima facie evidence of the sub-optimality of those schemes. As the initial shock of the pandemic recedes, we might expect to see its effects on mental health, in particular, become more pronounced as its economic effects recede.

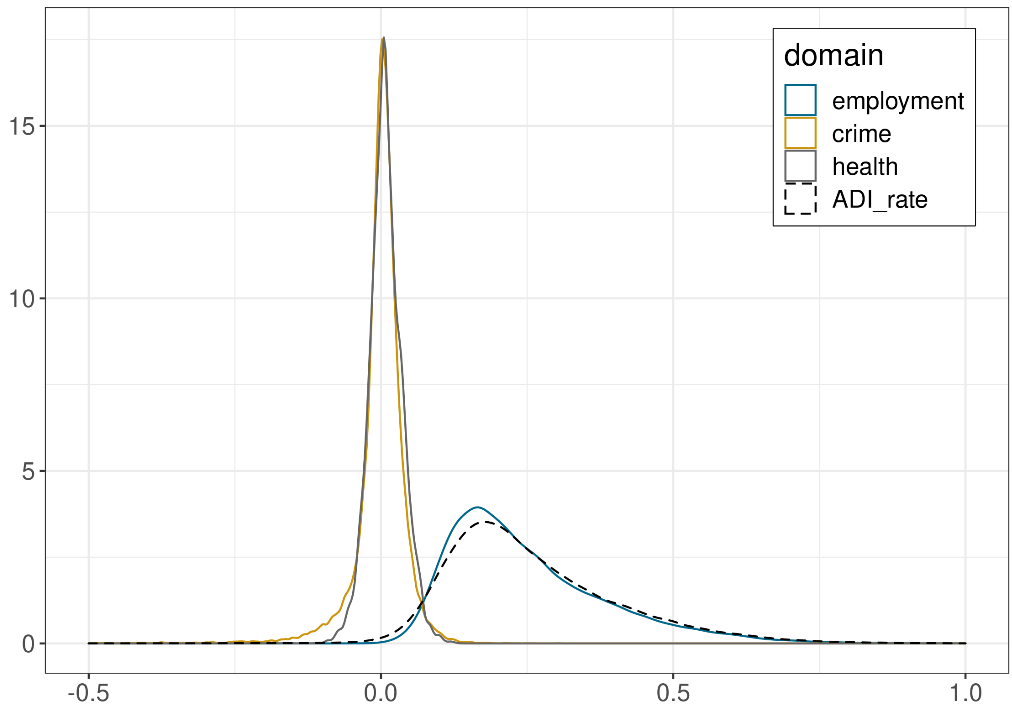


Figure 6: Kernel density estimates of changes in normalised deprivation cases between 2019 and 2020, for each of the three deprivation domains and the overall ADI. For definitions, see the discussion in section 3.

6 Summary

We present an Annual Deprivation Index which can be usefully deployed as a higher-frequency complement to the IMD. While the latter uses a large amount of intra-year information on deprivation, at the expense of a low release frequency, the ADI uses less intra-year information on deprivation to allow a higher release frequency. Despite this, the ADI and IMD are highly correlated in the years in which the latter is released, suggesting that there is little lost, and much gained, by the use of a lower-complexity, higher-frequency deprivation index.

Unlike the IMD, the ADI has a cardinal interpretation, and thus provides information on changes in deprivation for each neighbourhood over time. We take advantage of this aspect of the ADI to examine the impact of the Covid-19 epidemic on deprivation in England. We demonstrated that deprivation increased across the country, but that the greater effects were felt in cities and the coastal periphery. In other words, the impact of the Covid-19 epidemic on deprivation in England seems to have largely followed the same pattern of deprivation that has existed in England since the onset of de-industrialisation.

The cardinal nature of the ADI also means that the it does not suffer from rank reversal, and indeed does not suffer from any of the well-known problems of rank-based indices. This method might permit an improvement in the IMD methodology over time, if (for example) commensurable deprivation measures can be estimated in the education, housing and services, and living environment domains. Estimating such measures might also allow the number of domains in the ADI to increase in the future.

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A Additional information on health deprivation

As discussed in the main text, the health domain of the ADI uses information on mental health illnesses. However, the full ADI dataset available to users incorporates information on multiple afflictions. Specifically, we provide information on the prevalence the full set of afflications available from the QOF dataset:

1. Strokes,
2. Hypertension,
3. Diabetes,
4. Chronic obstructive pulmonary disease,
5. Epilepsy,
6. Hypothyroidism,
7. Cancer,
8. Mental health,
9. Asthma,
10. Heart failure,
11. Palliative care,
12. Dementia,
13. Chronic kidney disease,
14. Atrial fibrillation,
15. Obesity,
16. Learning disabilities,
17. Coronary heart disease,
18. Heart failure,
19. Depression,
20. Smoking,
21. Cardiovascular disease,
22. Peripheral arterial disease,
23. Osteoporosis,
24. Rheumatoid arthritis,
25. Non-diabetic hyperglycaemia.

These are all mapped from GP surgeries to lower-level super output areas using the methodology discussed in appendix B.

B Mapping GP surgery catchment areas to LSOAs

The ADI uses odata on list populations for a subset of GP surgeries in England available from the QOF dataset, and the populations within those lists that suffer from certain illnesses, which are assigned to LSOAs using a two-stage algorithm. The first-stage estimates the prevalence rate for each LSOA, and can be summarised as follows:

For each GP surgery:

1. Find the GP surgery's catchment area;
2. Compute the set of intersections of catchment area and surrounding LSOAs;
3. Compute the population of each intersection in this set, assuming LSOA populations are uniformly distributed;
4. Split the GP surgery's list population between each LSOA according to the population of each LSOA's intersection with the GP catchment area as a proportion of the total population;
5. Split the GP surgery's affected population between each LSOA according to the population of each LSOA's intersection with the GP catchment area as a proportion of the total population.

Denote the list population of GP k by L_k^{GP} and the affected population of GP k by Z_k^{GP}. Denote the population of LSOA i by P_i, the area of LSOA i by A_i, and the area of the intersection of LSOA i and GP k by A_{ik}. Finally, denote the population of the intersection between LSOA i and GP k by I_{ik}. Then our first-state algorithm computes:

$$I_{ik} = \left(\frac{A_{ik}}{A_i}\right) P_i, \tag{B.1}$$

$$L_i^{LSOA} = \sum_{k \in K(i)} \left(\frac{I_{ik}}{\sum_{j \in J(k)} I_{jk}}\right) L_k^{GP}, \tag{B.2}$$

$$Z_i^{LSOA} = \sum_{k \in K(i)} \left(\frac{I_{ik}}{\sum_{j \in J(k)} I_{jk}}\right) Z_k^{GP}, \tag{B.3}$$

in which $J(k)$ is the set of LSOAs that intersect with GP k, and $K(i)$ is the set of GP surgeries that intersect with LSOA i. We then have an estimated prevalence rate $R_i = Z_i/L_i$ for each LSOA, which is the final estimand of this stage.

Now, not all GPs are included in the prevalence statistics, not all GPs are included in the catchment boundary data, and total GP list sizes are not equal to the total population estimates. To arrive at a final set of estimates, we therefore use the following second-stage algorithm:

For each LSOA that does not intersect with a GP surgery: Estimate the prevalence rate using a simple weighted average of the prevalence rates of contiguous LSOAs;

For each LSOA: Compute the total number of affected patients by multiplying the LSOA's estimated prevalence rate by its estimated population.

The final estimate of the number of affected people in each LSOA is $N_i = R_i P_i$.

C Further comparison between the ADI and IMD

In this appendix we present three further comparisons of the ADI and IMD. The first, plotted in figure C.1 below, compares the geographies of the ADI and IMD ranks as of 2019. Specifically, this choropleth maps the difference between the IMD and ADI ranks as of 2019, in which a lower rank indicates higher deprivation. Hence, a neighbourhood in which the IMD rank is low (more deprived) but the ADI rank is high (less deprived) will have a negative difference. It is obvious from this figure that neighbourhoods in rural peripheries, e.g., rural Cornwall and the coasts of Lincolnshire and Norfolk, are more deprived according to the IMD, but less deprived according to the ADI.

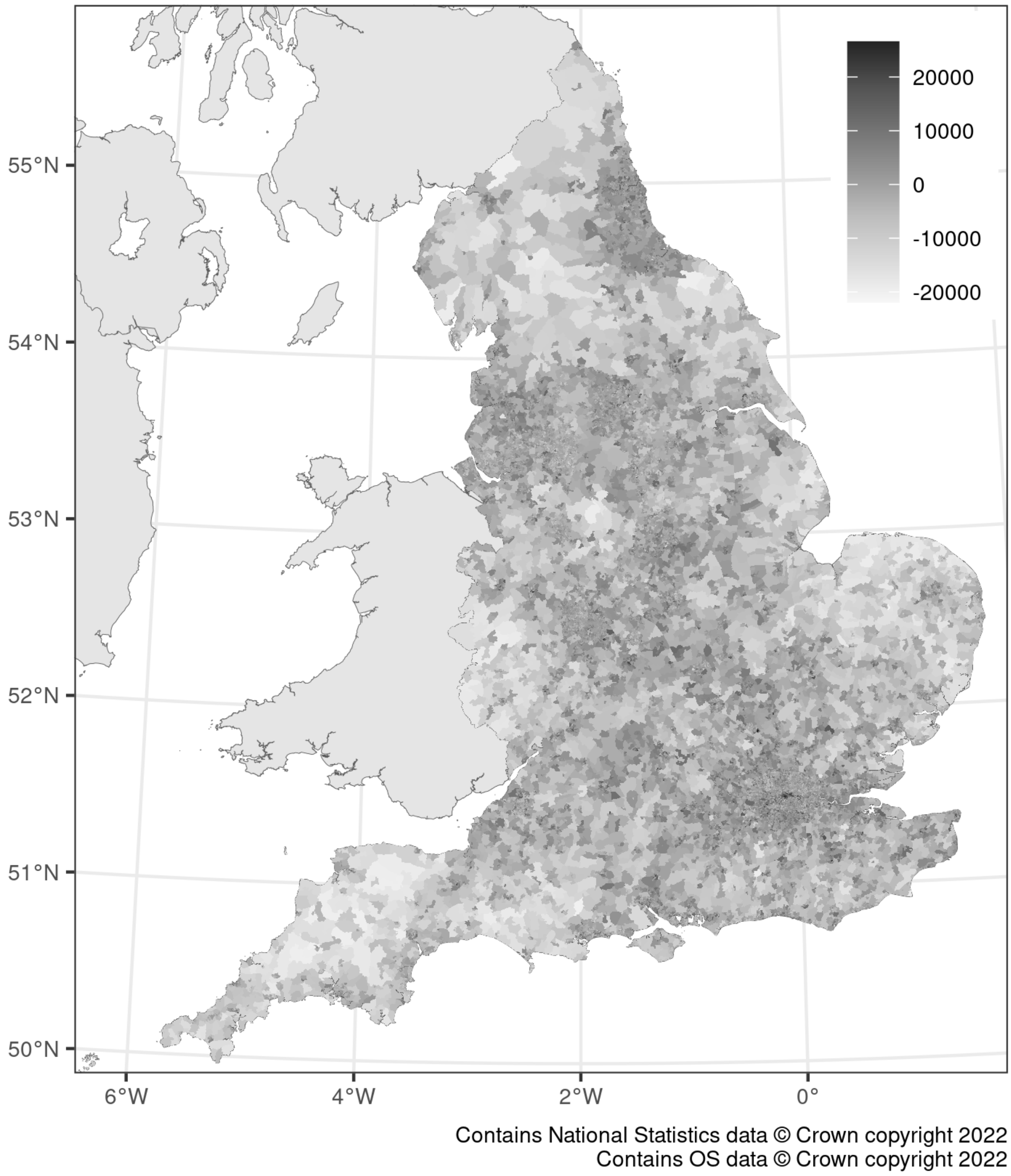

Figure C.1: Normalised ADI choropleth, 2020 data.

The second comparison groups the overall ADI and IMD datasets by local authority, and compares local authorities by the average rank of their constituent lower-level super output areas. This is one of the more straightforward ways that local authorities are summarised in the IMD dataset. Specifically, figure C.2 below plots a scatter of the average ADI rank versus average IMD rank across English local authorities, as of 2019. Clearly, local authority deprivation profiles are similar in the ADI and IMD, according to this method of summarising deprivation. In fact, the Pearson correlation between the two averages is 0.87.

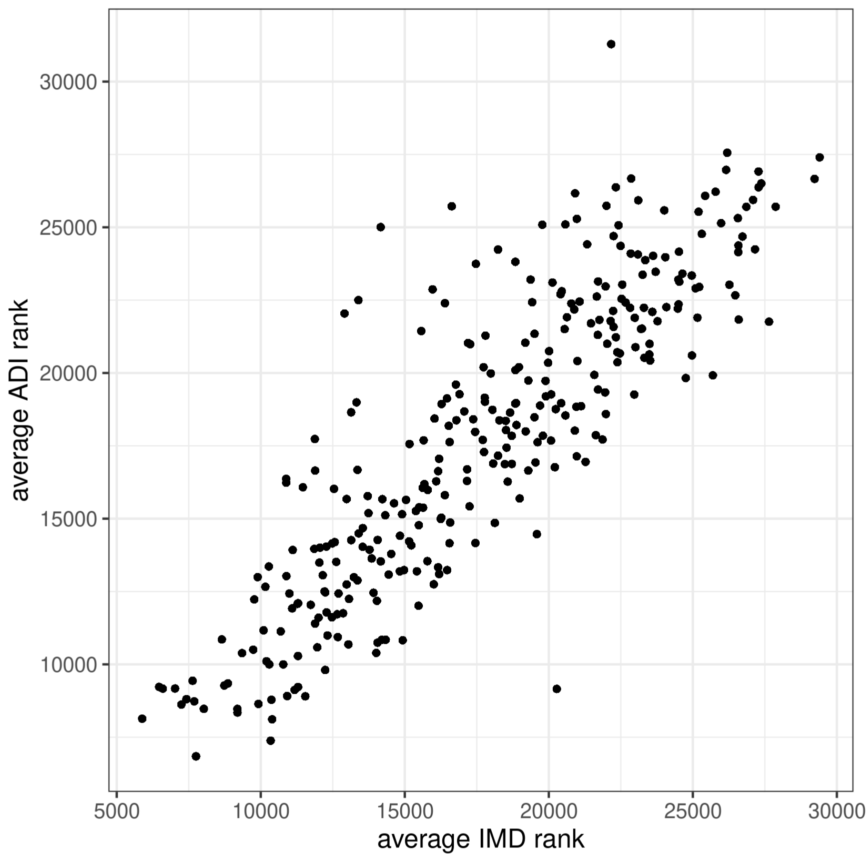

Figure C.2: Scatter of average IMD rank against average ADI rank, 2019 data.

The final comparison, summarised in table C.1, analyses the first 70 local authority districts assigned to the government's High Streets Task Force (which can be found at `https://www.highstreetstaskforce.org.uk/news/70-local-authorities-to-benefit-from-high-streets-task-force-support/`) by their ADI rank. The average ADI rank of these districts is 53, out of 317 districts in total, and 69% of the 70 most deprived districts according to the ADI were part of the initial High Streets Task Force districts.

We should not expect a complete overlap between the 70 most deprived districts according to the ADI and those assigned to the High Streets Task Force, as the latter also took into account measures of retail exposure to Covid-19. Nonetheless, there are districts in table C.1 which were presumably in need of support, but did not receive it. Moreover, as of 2020, there were 283 districts with a mean ADI measure greater than or equal to the least deprived of the High Streets Task Force districts. This is a straightforward consequence of the significant increase in deprivation experienced between 2019 and 2020.

Table C.1: 2019 ADI ranks of the first 70 local authority districts assigned to the High Streets Task Force.

Local Authority	High Street Task Force	ADI Rank	Local Authority	High Street Task Force	ADI Rank
City of London	0	1	Derby	1	65
Blackpool	1	2	Peterborough	1	66
Hartlepool	0	3	Hounslow	0	67
Middlesbrough	1	4	Lancaster	0	68
Birmingham	0	5	Wirral	1	69
South Tyneside	1	6	Medway	0	70
Burnley	1	7	Newham	1	71
Kingston upon Hull, City of	1	8	Barnsley	1	72
Blackburn with Darwen	1	9	Norwich	1	73
Thanet	1	10	Enfield	1	74
Darlington	1	11	Telford and Wrekin	0	75
Wolverhampton	1	12	Nuneaton and Bedworth	0	76
Newcastle upon Tyne	1	13	Rotherham	1	77
Sunderland	1	14	Dudley	0	78
Nottingham	1	15	Carlisle	0	79
Bradford	1	16	Greenwich	0	80
Westminster	0	17	Ealing	0	81
Liverpool	1	18	Bedford	0	82
North East Lincolnshire	1	19	Tameside	1	83
Hastings	1	20	Plymouth	1	84
Manchester	0	21	Mansfield	1	85
Gateshead	1	22	Folkestone and Hythe	0	86
Knowsley	0	23	Thurrock	0	87
Hyndburn	0	24	Chesterfield	0	88
Stockton-on-Tees	1	25	Rossendale	0	89
Southwark	0	26	Gloucester	0	90
Redcar and Cleveland	1	27	Waltham Forest	0	91
Preston	0	28	Pendle	1	92
Stoke-on-Trent	1	29	Tendring	1	93
Halton	1	30	Barrow-in-Furness	1	94
Lincoln	1	31	Basildon	0	95
Great Yarmouth	1	32	Kensington and Chelsea	0	96
Tower Hamlets	1	33	Wigan	1	97
County Durham	1	34	Slough	0	98
Sandwell	0	35	Worcester	0	99
Croydon	0	36	Luton	1	100
Lambeth	1	37	Erewash	0	101
Hackney	1	38	Wakefield	1	102
Barking and Dagenham	1	39	North Lincolnshire	0	103
Bolton	1	40	Brent	1	104
Hammersmith and Fulham	0	41	Camden	0	105
St. Helens	1	42	Northampton	0	106
Harlow	0	43	Portsmouth	1	107
Haringey	1	44	Reading	0	108
Oldham	1	45	Redditch	0	109
Lewisham	1	46	Bristol, City of	1	110
Walsall	1	47	Sheffield	1	111
Calderdale	1	48	Northumberland	0	112
Swale	1	49	Bury	0	113
Islington	1	50	Brighton and Hove	0	114
Corby	1	51	Ashfield	1	115
Southampton	1	52	Watford	0	116
Doncaster	1	53	Crawley	0	117
North Tyneside	0	54	Eastbourne	0	118
Kirklees	0	55	Copeland	0	119
Southend-on-Sea	0	56	East Lindsey	1	120
Sefton	1	57	Bassetlaw	0	121
Leeds	1	58	Sedgemoor	0	122
Salford	0	59	Coventry	0	123
Leicester	1	60	Wellingborough	0	124
Ipswich	1	61	Ashford	0	125
Gravesham	0	62	Solihull	0	126
Dover	0	63	Torbay	1	127
Rochdale	1	64	Allerdale	0	128
			Scarborough	1	129