The Good Life: Measuring inclusive growth across communities

Technical Appendices

Technical Appendix 1: Methodology of the CPP Inclusive Growth Community Index

The CPP Inclusive Growth Community Index follows closely the methodology developed for the country level index.[1] In doing so, we continue to build on the work of Stanford University economists Charles Jones and Peter Klenow.[2] Their methodology uses the economics of expected utility to produce a consumption equivalent measure of welfare for a range of countries relative to the US. It estimates lifetime expected utility based on consumption, inequality, leisure time and life expectancy. We produce our inclusive growth score for the community index by adapting this in a number of ways:

- We add in a term for unemployment
- We use healthy life expectancy instead of life expectancy
- We adjust the leisure score so that additional non-working time due to unemployment is not counted as leisure

We then apply the approach to upper tier local authorities in the UK, using the UK average as a baseline, rather than the US as in the country index.

Original Jones and Klenow methodology[3]

The Jones and Klenow macro methodology formulation gives a lifetime utility that is the product of life expectancy and expected flow utility from each year. For a given country, i, this gives:

(1) $U_i = e_i(\bar{u} + log\ c_i + v(l_i) - \frac{1}{2}\sigma_i^2)$

Where: U_i = expected lifetime utility, $\bar{u}$ = an intercept term calibrated represent to the annual value of remaining life of a 40-year-old in the United States, e_i= life expectancy, c_i = consumption, $v(l_i)$ = utility of leisure and home production and σ_i^2 = variance of log consumption in country i.

Jones and Klenow produce a welfare statistic by asking what factor, λ_i, consumption in the US must be adjusted by to make the average consumer indifferent to living the rest of their life in country i and the US. This can be expressed as consumption equivalent welfare:

(2) $U_{us}(\lambda_i) = U_i(1)$

Where: λ_i = welfare in country i.

[1] Norman, A. et al. (2019) *The Good Life: Measuring inclusive growth across countries*. Available at: https://www.progressive-policy.net/downloads/files/CPP_The_Good_Life.pdf
[2] Jones, C. and Klenow, P. (2016) *Beyond GDP? Welfare across Countries and Time*. American Economic Review, 106 (9): 2426-57. Available at: https://www.aeaweb.org/articles?id=10.1257/aer.20110236
[3] For the full algebraic calculation please see the full Jones and Klenow paper

Using equations (1) and (2) to produce an expression for the welfare index gives:

(3) $log\lambda_i = \frac{e_i - e_{us}}{e_{us}}\left(\bar{u} + \log c_i + v(l_i) - \frac{1}{2}\sigma_i^2\right)$	*Life expectancy*
$+ \log c_i - \log c_{us}$	*Consumption*
$+v(l_i) - v(l_{us})$	*Leisure*
$-\frac{1}{2}(\sigma_i^2 - \sigma_{us}^2)$	*Inequality*

This yields an additive decomposition of the factors that determine the log of welfare in country i, relative to the US.

CPP adjustments to the Jones and Klenow methodology

For the community index we calculate welfare in local authority i, relative to the UK average. We also make the following adjustments.

Adding in unemployment:

Our methodology builds on the original Jones and Klenow methodology by including additional negative impacts of unemployment. Our assumption is that unemployment has additional disutility beyond its impact on consumption and consumption inequality. Being unemployed has a negative effect on welfare in and of itself.

We assume that this additional negative impact of unemployment on an individual is a fixed utility, $\overline{DU}$, that applies regardless of income, country, time or anything else. (See the following section for quantifying this fixed utility impact.)

Adding this into (1) gives:

(4) $(U_i = e_i(\bar{u} + \log(c_i) + v(l_i) + \bar{x} - (ur_i * \overline{DU}) - \frac{1}{2}\sigma_i{}^2)$

Where ur_i is the unemployment rate (as a % of total population) in country i and $\overline{DU}$ is the disutility of being unemployed for a given year. Our unemployment term is thus

(5) $w(z_i) = ur_i * \overline{DU}$

Note that we have also added an additional constant, $\bar{x}$. This is set so that the addition of the unemployment term does not affect utility in the base country, the US.

Adding the disutility of unemployment into (3) gives:

(6) $log\lambda_i = \frac{e_i - e_{us}}{e_{us}}\left(\bar{u} + \log(c_i) + \bar{x} + w(z_i) + v(l_i) - \frac{1}{2}\sigma^2\right)$

$+ \log(c_i) - \log(c_{us})$

$+ w(z_i) - w(z_{us})$

$+ v(l_i) - v(l_{us})$

$-\frac{1}{2}(\sigma_i^2 - \sigma_{us}^2)$

Using healthy life expectancy rather than life expectancy:

We switch from using life expectancy in the country index to using healthy life expectancy (number of years living in good health) in the community index, following feedback on our initial approach. This reflects the importance of measuring healthy lives rather than simply life spans.

We make no specific adjustments to the weightings to account for this change due to a lack of available data on the welfare benefits of healthy life expectancy versus life expectancy. Logically the value of an average healthy year of life will be higher than the value of an average year of life. As such, it is likely that the index slightly undervalues differences in healthy life expectancy.

Inequality:

We do not make Jones and Klenow's simplifying assumption that consumption is lognormally distributed which allows them to define the inequality term in terms of consumption variance or Gini coefficient. Instead we calculate the inequality terms directly from the consumption distribution defined in terms of deciles. We assume consumption is equal within deciles.

We continue to use Jones and Klenow's underlying convention that the consumption term represents the expected utility of consumption were it to be equally distributed and the inequality term represents the degree to which expected utility of consumption is actually less than this due to its uneven distribution.

Data sources and calibration[4]

Consumption:

By consumption we mean household equivalized consumption, including benefits in kind,[5] and excluding housing costs. As there is no available data on the distribution of consumption at the local level we estimate it based on local authority data on income distribution and a model of the relationship between consumption and income.

The local authority income distribution data is resident's earnings by decile from the Annual Survey of Hours and Income (ASHE) for the relevant year, converted to real terms.[6] A small number of datapoints in this source are unavailable. We estimated these based on available data points for the local authority in question, and the national relationship between deciles.

The income-consumption model is based on their 2016 relationship across national income deciles. National income by decile is taken from ASHE, as above. Consumption deciles come from CPP analysis of the Effects of Taxes and Benefits on Household Income dataset, summing

[4] Please see full Jones and Klenow paper for more detail on the assumptions underpinning the weights used in our model.

[5] Benefits in kind (BIK) are notional benefits provided to households by the Government. It includes education, the NHS, housing subsidy, rail travel subsidy, bus travel subsidy, school meals and healthy start vouchers.

[6] Specifically, we use the "weekly pay – gross" variable for all (full and part-time) workers. Extracted from NOMIS at: https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=30

household consumption and benefits in kind.[7] There is a clear linear relationship across the deciles (the R^2 is 0.999) given by y=1.07x+173.25 (where y = consumption and x = income). This is applied to convert local income data to consumption. This method will not capture local variations in consumption that are not related to income. The data is normalised around the UK average.

Differences in housing costs between areas are likely to be driven by geographic price differences more than quality or quantity differences. We therefore exclude housing (rent and mortgage interest) from our consumption figures using proportions estimated at a regional level from ONS family spending data.[8] These range from 15% in London to 4% in Northern Ireland.

Inequality:

Inequality is calculated from the consumption distribution dataset, as described above.

Healthy life expectancy:

Healthy life expectancy data is obtained from the ONS Health state life expectancy dataset. We use an average of the male and female figures, and use the 2015-2017 figure to represent 2016 etc. We set $\bar{u}$ as equal to 5.2325, as per Jones and Klenow.

Leisure:

As per Jones and Klenow, leisure is defined as the proportion of waking hours (set at 16 per day) not spent in work. This means that it includes home production and other activities that may not be considered leisure. Formally, we define leisure (l) as:

$$(7)\quad l = 1 - \frac{annual\ hours\ worked\ per\ worker}{16 \times 365} \times \frac{employment}{adult\ population}$$

Utility from leisure is set such that:

(8) $v(l) = -\frac{\theta\varepsilon}{1+\varepsilon}(1-l)^{\frac{1+\varepsilon}{\varepsilon}}$ where ε= Frisch elasticity of labour supply, $1-l$ is the labour supply and θ is the utility weight on leisure. We use the Jones and Klenow values, such that θ = 14.2 and ε = 1.[9]

Data on hours worked per worker comes from ASHE and employment and population data comes from the Annual Population Survey.

We then adjust the hours worked per worker figures so that additional non-working time due to unemployment is not counted as leisure. This is done by adding hours per worker multiplied by the unemployment rate.

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[7] Specifically, we sum the *Total Benefits in Kind* and *Total Household Expenditure consistent with Disposable Income* variables, weight, across the *Decile Groups of Equivalised Disposable Income (Modified-OECD Scale)* variable. Source: UK Data Archive (2018) *Study Number 8421 - Effects of Taxes and Benefits on Household Income, 2016-2017*

[8] ONS (2019) *Family spending in the UK: April 2017 to March 2018.* Table A35. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/bulletins/familyspendingintheuk/financialyearending2018

[9] Please see full Jones and Klenow paper for full explanation of these values

Unemployment:

$\overline{DU}$ represents the disutility of unemployment for an individual over and above the impact on their income and consumption. We calibrate this value by looking at the amount of additional consumption that is required to have the same positive impact on life satisfaction as employment does relative to unemployment. Specifically, we use the Clark and Oswald (2002) finding that the disutility effect of unemployment is equivalent to £180,000 of additional income per year.

Formulating this approach with our earlier utility function (4), we state that expected utility when not unemployed, with a base level of consumption (C_{Base}) is equivalent to expected utility when unemployed but with additional consumption (C_{Extra}) to compensate this:

(9) $\bar{u} + \log(C_{Base}) + v(l_a) + \bar{x} - 0 * UP - \frac{1}{2}\sigma_i{}^2 = \bar{u} + \log((C_{Base} + C_{Extra})) + v(l_a) + \bar{x} - 1 * UP - \frac{1}{2}\sigma_i{}^2$

This can be rearranged to:

(10) $\overline{DU} = \log((C_{Base} + C_{Extra})/C_{Base})$

From Clark and Oswald (2002), using income as a proxy for consumption, we take C_{Extra} as £180,000 per year and C_{Base} as £24,000, the average household income from the study. This gives:

(11) $\overline{DU} = \log(\frac{180{,}000+24{,}000}{24{,}000})$

This gives a $\overline{DU}$ value of 2.14.

We also add a constant $\bar{x}$ so that the addition of the unemployment term does not affect the level of utility in the base case, the UK average. This means $w(z_{UK}) + \bar{x} = 0$, i.e:

(12) $\bar{x} = ur_{UK} * \overline{DU}$

Unemployment rate data is from the Annual Population Survey and includes those aged 16+. This is adjusted to equal percentage of the total population.

Data

The full data for the final rankings is available upon request.

Technical appendix 2: Understanding how local area characteristics relate to inclusive growth

Background and motivation

In the report, *The Good Life: Measuring inclusive growth across communities,* we argue that inclusive growth is a process whereby places seek to drive forward shared prosperity through policies that address specific priority challenges in their areas. But since there is no consensus on what inclusive growth is or how to measure it, there is also no consensus on how to identify the priority issues that areas should focus on to boost inclusive growth. To help fill this gap, our research has 1) developed a new measure of inclusive growth at the local level and 2) explored which local area characteristics are associated with higher or lower levels of inclusive growth. In this context, this appendix explains how we have identified local area characteristics and their statistical associations with levels of inclusive growth.

Methodology

To better understand local area characteristics, we utilise statistical methods that organise and group many diverse indicators. We then assess the correlations between where local areas rank on the characteristics and their inclusive growth score. To achieve this aim, we broadly follow the series of steps set out by the European Commission's "Composite Indicators Research Group". To summarise, these include:

1. *Selecting the variables*: We selected variables that might have a relationship with the inclusive growth outcomes measure. As a first step, we explored the data availability for indicators that are included within inclusive growth frameworks for Greater Manchester and the West Midlands Combined Authority. We gathered data on variables using the Public Health England fingertips database, the Annual Population Survey and the ONS for 151 upper tier local authorities for 2016-17. Unfortunately, not all variables were available for all authorities and so 21 observations were dropped from our data. Our final sample consists of 25 variables across 130 local authorities in 2016-17. Definitions and data sources for all variables can be found at the end of this note.
2. *Standardisation*: The variables use many different units of measurement. All variables are therefore standardised by subtracting the mean and dividing by the standard deviation.
3. *Multivariate analysis*: We applied a statistical technique called principal component analysis (PCA) to reduce the complexity of the data. This means grouping together variables that are strongly associated with each other, while rarely associated with others, so that the final groups refer to different local authority characteristics.
4. *Normalisation*: Since the values derived through PCA are hard to interpret, we rank each local authority based on its scores between 0 and 1.
5. *Regression analysis*: We perform multivariate regression analysis to explore the relationships between local authority characteristics and the inclusive growth outcomes measure. Given our methodology, the relationships we show are purely descriptive; however, they provide an indication of the key issues facing areas that score poorly on inclusive growth while conversely pointing to areas of success for high performing local authorities.

Local area characteristics

Based on the above steps we identify 14 broad groups (or characteristics) against which we can rank local areas. These groups explain approximately 80% of the variation in the data we collected. In order to describe the defining features of the different groups, we explore the coefficients for the variables. The groups are organised by theme: work and jobs, natural and the built environment, vulnerability, and education and skills.

The defining features of each group are:

<u>Work and jobs</u>

Vibrant labour markets: higher proportion of good jobs and fewer claimants and fewer long-term claimants.

Fewer jobs, greater sickness: lower job density and greater sickness absence.

Fewer NEETS, smaller gender pay gap: lower proportion of NEETS and lower gender pay gap

Fewer jobs, larger employment gap for health: lower job density and higher gap between employment rate for people in poor health and rest of the population.

Mind the gap: lower job density, lower health and mental health related employment gap.

<u>Natural and built environment</u>

Expensive homes and more pollution: higher air pollution and less affordable housing

Less utilisation of space: lower proportion of people taking a visit to the natural environment for health or exercise purposes.

Higher access to woodland: higher proportion of people with accessible woodland.

<u>Vulnerability</u>

Greater vulnerability for all: higher first-time offenders and people going through the youth justice system, more fuel poverty and children in care.

Better for young and old but higher homelessness: lower social isolation for older people and fewer children in care but higher rates of homelessness.

Higher isolation, more young offenders: higher social isolation for older people and more going through the youth justice system.

<u>Education and skills</u>

Good education for young and old: higher rates of school readiness, higher average attainment 8 and higher lifelong learning.

Fewer qualifications: higher proportion of people with no qualifications and lower proportion of people with NVQ4+.

Good education for young, poor for old: lower proportion of people lifelong learning but higher average attainment 8.

How the groups relate to IG outcomes

To understand the relationship between the above groups and inclusive growth, we ran a multivariate regression model with the IG score as the dependent variable and the groups as independent/control variables. The model is a good fit for the data explaining 80% of the variation in IG scores across local areas. As the results in table 1 show, the *vibrant labour markets* and *greater vulnerability for all* groups have by far the largest relationships with the IG score after controlling for other groups. Several other groups also have statistically significant associations with the IG score, but the coefficients are comparatively small. The two main groups - vibrant labour markets and greater vulnerability for all - are therefore by far the most important in explaining local variation in IG score. This is underlined by the fact that if we just regress these two groups on the IG score, this still explains over 70% of the local area variation in IG.

Table 1. Regression of groups on IG score

	Coefficient	*Standard Error*	*t Stat*	*P-value*
Vibrant lab market	0.445	0.074	6.03	0.00
Intercept	0.367	0.084	4.37	0.00
Fewer qualifications	0.095	0.043	2.23	0.03
Good education for young and old	0.094	0.068	1.39	0.17
Fewer NEETS, smaller gender pay gap	0.085	0.044	1.90	0.06
Good edu for young, poor for old	0.077	0.044	1.76	0.08
Better for young and old but higher homelessnes	0.061	0.076	0.81	0.42
Higher isolation, more young offenders	0.058	0.046	1.24	0.22
Expensive homes and more pollution	0.058	0.083	0.70	0.49
Less utilisation of space	0.038	0.042	0.91	0.36
Higher access to woodland	-0.031	0.043	-0.71	0.48
Fewer jobs, larger empl gap for ill health	-0.045	0.052	-0.86	0.39
Mind the health and mental health gap	-0.144	0.047	-3.07	0.00
Fewer jobs, greater sickness	-0.163	0.047	-3.45	0.00
Greater vulnerability for all	-0.357	0.058	-6.16	0.00

Notes: If a group is highlighted blue, it means has a statistically significant relationship with the IG score.

Implications

Those local authorities which score highly for *vibrant labour markets* also tend to do very well on inclusive growth. These areas are characterised by a higher proportion of good jobs, and a lower proportion of claimants and long-term claimants. Local authorities scoring highly on this group include: West Berkshire, Windsor and Maidenhead and Buckinghamshire – all of which also do well on the inclusive growth score. By contrast, those local authorities which score highly for *greater vulnerability for all* also tend to do badly on inclusive growth. These areas are characterised by: more people entering the youth justice system and first-time offenders, higher fuel poverty and more children in care. Local authorities scoring highly on this group include: Wolverhampton, Newham and Stoke on Trent – all of which also score badly for inclusive growth.

While the results do not demonstrate causation between local area characteristics and inclusive growth, they do show the sorts of challenges that are particularly acute for local areas that score badly and conversely the sorts of issues that high scoring local authorities are performing particularly well on. For low scoring areas, supporting children in care, reducing poverty, lowering crime rates and supporting young offenders are likely to be critical challenges. For high scoring areas, the importance of good work comes through very strongly. For local authority rankings on these groups please see the dataset accessible via our website.

Data

Data for the variables used to create the local area characteristics were sourced from the Public Health England Fingertips database, the ONS' Annual Population Survey (accessed via NOMIS), and the ONS. The table below provides definitions for each of the variables used in our analysis and their original sources.

Headline data on how local areas rank on these groupings is available to download from our website.

Variable ID	Indicator	Definition	Source
Job.den	Job density	The number of filled jobs in an area divided by the resident population aged 16-64 in that area (e.g. a job density of 1.0 is one job per person aged 16-64). Total jobs inc.: employees, self-employed, government supported trainees and the armed forces.	PHE fingertips. Original source: ONS, accessed via nomis.
Good.job	Proportion of economically active adults in a good job.	Data on good jobs comes from a user request to the ONS. It includes those employed on a permanent contract or are employed on a temporary contract but are not seeking permanent employment, earn at least two thirds of the UK median hourly wage, work less than 49 hours a week and are not unwillingly working part-time (e.g. because they could not find a full-time job).	The full dataset can be downloaded at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/adhocs/007601estimatedproportionofeconomicallyactiveadultsinagoodjobcustomerdefinedandestimatedproportionoflifelonglearnersukthreeyearsendingdecember2016
Life.long.learning	Proportion of adults participating in post-continuous education	Data on lifelong learning comes from a user request to the ONS. The statistic refers to adults who have completed continuous full-time education and then return to participate in education/training. The population used to calculate the statistic are adults (aged 16+) who have completed continuous full-time education (i.e. returned to education/training after at least a year break in which they did not participate in full-time education). The criteria for 'participation in post-continuous adult education' is defined as: an individual who is currently working or studying towards a qualification, or who is undertaking an apprenticeship, or who have completed an education or training programme in the last 4 weeks.	The full dataset can be downloaded at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/adhocs/007601estimatedproportionofeconomicallyactiveadultsinagoodjobcustomerdefinedandestimatedproportionoflifelonglearnersukthreeyearsendingdecember2016
Access.to.woodland	Access to woodland	Percentage of the population in each local authority that has accessible woodland of at least 2 hectare within 500 metres of where they live	PHE fingertips Original source: Woodland trust - Woodland Indicators by local authority
Gender.pay.gap	Gender pay gap (by workplace location)	The absolute difference between median gross hourly earnings (excluding overtime) of men and women as a proportion of median gross hourly earnings (excluding overtime) of men, presented as a percentage. The value implies male earnings are greater than female earnings unless noted otherwise. Based on earnings by workplace location.	PHE fingertips Original source: Annual Survey of Hours and Earnings (ASHE), Office for National Statistics
Utilisation.of.outdoor.space	Utilisation of outdoor space for exercise/health reasons	The weighted estimate of the proportion of residents in each area taking a visit to the natural environment for health or exercise purposes.	PHE fingertips Original source: Natural England: Monitor of Engagement with the Natural Environment (MENE) survey

		This does not include: • routine shopping trips or; • time spent in own garden	
NEETS	16-17 year olds not in education, employment or training (NEET) or whose activity is not known	Proportion of 16-17 year olds not in education, employment or training (NEET) or whose activity is not known.	PHE fingertips Original source: Department for Education
Children.in.care	Children in care	Children looked after at 31 March (rate per 10,000 population aged under 18 years)	PHE fingertips Original Source: Children looked after in England, Department for Education.
Sickness.abs	Sickness absence – the percentage of employees who had at least one day off in the previous week	Percent of employees who had at least one day off due to sickness absence in the previous working week.	PHE fingertips Original source: Labour Force Survey – Data provided by ONS
No.qual	Proportion of the population with no qualifications	% with no qualifications - aged 16-64	ONS Annual population survey. Accessed via NOMIS.
Air.poll	Air pollution: fine particulate matter	Annual concentration of human-made fine particulate matter at an area level, adjusted to account for population exposure. Fine particulate matter is also known as $PM_{2.5}$ and has a metric of micrograms per cubic metre (µg/m3).	PHE fingertips Original source: Defra: various instruments used to derive estimates including Pollution Climate Mapping model, Automatic Urban and Rural Network and National Atmospheric Emissions Inventory. Also makes use of census population estimates (ONS). See https://uk-air.defra.gov.uk/data/pcm-data#population_weighted_annual_mean_pm25_data for more detail.
Affordhomeown	Affordability of home ownership	Ratio of median house price to median gross annual residence-based earnings (A higher ratio indicates that on average, it is less affordable for a resident to purchase a house in their local authority district)	Original source: Data is sourced from the ONS and based upon House Price Statistics for Small Areas (HPSSAs) and Annual Survey of Hours and Earnings data.

Housingafford	Housing affordability ratio	The ratio of lower quartile house price to lower quartile earnings	PHE fingertips Original source: Department for Communities and Local Government
Youth.justice.system	First time entrants to the youth justice system	Rates of juveniles receiving their first conviction, caution or youth caution per 100,000 10-17 year old population by area of residence.	PHE Fingertips Original source: https://www.gov.uk/government/statistics/criminal-justice-system-statistics-quarterly-december-2017
Gap.in.the.employ.mental.health	Gap in the employment rate for those in contact with secondary mental health services and the overall employment rate	The percentage point gap between the percentage of working age adults who are receiving secondary mental health services and who are on the Care Programme Approach recorded as being employed (aged 18 to 69) and the percentage of all respondents in the Labour Force Survey classed as employed (aged 16 to 64)	PHE fingertips Original source: ONS Annual Population Survey and NHS Digital
Claimaints	Employment and Support Allowance claimants	The percentage of the population aged 25-34 years claiming Employment and Support Allowance (ESA), Incapacity Benefit (IB) or Severe Disablement Allowance (SDA)	PHE fingertips Original source: nomis: https://www.nomisweb.co.uk/
Gap.in.the.employ.health	Gap in the employment rate between those with a long-term health condition and the overall employment rate	The percentage point gap between the percentage of respondents in the Labour Force Survey who have a long-term condition who are classified as employed (aged 16-64) and the percentage of all respondents in the Labour Force Survey classed as employed (aged 16-64)	PHE fingertips Original source: ONS Annual Population Survey.
Long.term.claimants	Long term claimants of Jobseeker's Allowance	Count for jobseekers allowance claimants, 16-64 year olds claiming for more than 12 months, crude rate per 1,000 resident population, 16-64 year olds.	PHE fingertips. Original source: www.nomisweb.co.uk Data selection 'Jobseeker's Allowance' Numerator: 'Jobseeker's Allowance by age and duration - Age Duration - 'Claiming for over 12 months'. Denominator: 'Claimant count denominators - current residents / workforce series'

School.readiness	School Readiness: the percentage of children achieving a good level of development at the end of reception	Children defined as having reached a good level of development at the end of the Early Years Foundation Stage (EYFS) as a percentage of all eligible children.	PHE fingertips Original Source: Department for Education (DfE), EYFS Profile: EYFS Profile statistical series
NVQ4	Proportion of the population with NVQ level 4+ qualifications	% with NVQ4+ aged 16-64	ONA annual population survey. Accessed via NOMIS.
Homelessness	Statutory homelessness – households in temporary accommodation	Households in temporary accommodation, crude rate per 1,000 estimated total households, all ages, snapshot at 31^{st} March, persons	PHE fingertips Original Source: Ministry of Housing, Communities & Local Government
Fuel.poverty	Fuel poverty	The percentage of households in an area that experience fuel poverty based on the "Low income, high cost" methodology.	PHE fingertips Original source: Department for Business, Energy and Industrial strategy
First.time.offenders	First time offenders	Rate of first-time offenders based on recorded via Police National Computer crime data per 100,000 population.	PHE fingertips Original source: Ministry of Justice
Average.attainment.8.score	Average Attainment 8 score	Average Attainment 8 score for all pupils in state-funded schools, based on local authority of pupil residence.	PHE fingertips Original source: Data downloaded from the Department for Education website: https://www.gov.uk/government/statistics/gcse-and-equivalent-results-2016-to-2017-provisional.
Social.isolation	Social Isolation: percentage of adult social care users who have as much social contact as they would like	The percentage of respondents to the Adult Social Care Users Survey who responded to the question "Thinking about how much contact you've had with people you like, which of the following statements best describes your social situation?" with the answer "I have as much social contact as I want with people I like".	PHE fingertips Original source: Adult Social Care Survey - England