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Measuring Disadvantage

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KEY FINDINGS

• A major challenge when contextualising admissions to university, or recruitment for jobs, is access to high quality information on a young person's background, to identify those who should benefit. Granular and verifiable information about prospective students' socio-economic background is, in practice, limited. As a consequence, universities and employers often need to use 'proxy' measures, for example looking at the local area someone grew up in based on their home postcode. But little is known about how well these measures capture individual-level socio-economic status.

• This report uses data from the Millennium Cohort Study to look at how various proxies for family background correlate with long-run family income, based on data for over 7,000 children.

• The **number of years a child has been eligible for free school meals** is the best available marker for childhood poverty (Pearson correlation = 0.69) and is therefore likely to be the best indicator for use in contextual admissions. FSM eligibility also has fewer biases then other measures, particularly for single parent families and renters who are more often missed by other measures. However, verified data on FSM eligibility is not currently available to universities.

• Until this happens, they will need to continue to use area level markers. **POLAR**, an indicator of university participation by local area, is currently a key measure used in contextual admissions in the UK. However, it was not designed to measure socio-economic disadvantage, and is very poorly correlated with low family-income (correlation = 0.22). It is also biased against key demographic groups, including BAME students. Similarly, **TUNDRA**, an experimental alternative to POLAR, is also a poor measure of income deprivation (correlation = 0.17), and suffers from similar biases. Both POLAR and TUNDRA are unsuitable for use in contextual admissions.

• **ACORN** is the best area-level measure available, as it measures households at a very localised level (around 15 households), is designed to be comparable across the UK, and has a reasonably good relationship to low household income (correlation = 0.56). It is also slightly less biased than other area-based markers. However, as a commercial indicator, it is not free to use, and the methodology behind is it not openly published.

• The **Index of Multiple Deprivation (IMD)** is another good option for an area level marker with a moderate relationship with low household income (correlation = 0.47), and the benefit of being publicly available. However, the measure is biased against those who are BAME, live in a single parent household and who rent. IMD is also not comparable across the four constituent countries that form the UK.

• Parental education level, specifically whether someone is **first in family to attend university**, is also a common marker used by universities. FiF graduates are less likely to have a parent working in a higher managerial occupation (40% versus 85%), or who own their own home (76% versus 92%). However, a large proportion of recent graduates (about two thirds) are first in family, so the measure covers a fairly broad group. The marker also cannot be independently verified, so may be more suitable for lower-stakes decisions rather than determining contextual offers.

INTRODUCTION

Social mobility and equality of opportunity are now key public policy issues. Successive governments have attempted to improve educational and labour market opportunities for young people from disadvantaged backgrounds, though with varying degrees of success. One aspect of equalising opportunities is in improving access to higher education (HE), particularly to the most sought-after subjects and institutions. By doing so, it is hoped that this will help disadvantaged young people to gain access to the top professions, with both the status and the financial rewards that this brings.

Given this policy background, a major feature of university admissions is now their "widening access" programmes; schemes that are designed to provide extra opportunities to prospective students from underrepresented backgrounds to encourage them to apply for a university place. On increasingly important part of this work – particularly at high-tariff, high-status universities – is the use of contextual admissions. This is where lower grade offers are required by universities for young people from certain backgrounds (typically those who are underrepresented within the UK's top higher education institutions). The motivation for such schemes is that these perspective students have not had the same educational opportunities during their time at school as their peers from more affluent families. Yet they still have managed to achieve very good grades, and arguably have the same potential as their more advantaged peers. There is also some empirical evidence to back such arguments up, with previous research finding that schools with a large proportion of pupils eligible for Free School Meals (FSM) generate better degree outcomes than schools with a lower share of FSM pupils.[1] Specifically, the researcher notes how "*Once we compare individuals with similar levels of attainment, those from independent and selective state schools, those from state schools with a low proportion of FSM-eligible pupils and those from high-value-added state schools are now significantly more likely to drop out, significantly less likely to complete their degree and significantly less likely to graduate with a first or a 2:1 than their counterparts in non-selective state schools, state schools with a high proportion of FSM-eligible pupils and low-value-added state schools respectively*".

One of the challenges in implementing such contextual admission programmes is that they require high-quality information about a students' background; universities need to be able to accurately identify members of underrepresented groups if they are going to lower the entry grades they require of them. Unfortunately, the information available to universities about prospective students' socio-economic background is somewhat limited. Rather than being able to access high-quality and independently verifiable data on one of the three main individual-level socio-economic status indicators (family income, parental social class or parental education), information is often only available about their home postcode. This means that, in practice, proxy socio-economic indicators are used, with contextual admission offers often based upon the characteristics of the local area where young people live. A number of studies have criticised this approach,[2] with various suggestions made about potential alternative approaches that could be used instead (e.g. providing universities with access to government records about applicant's eligibility for FSM during their time at school). What this has led to is a confusing situation, where universities are now each using a basket of different indicators in different ways.

Yet there is relatively little empirical evidence about how well the various proxy indicators used by universities capture individual-level socio-economic status, and how they compare to one another in this respect. This is important as, if proxy measures are to be used to identify candidates for contextual admission programmes, it is vital we understand their relative strengths and limitations. In this report, I provide an overview of the evidence available, based upon the academic work presented in Jerrim (2020).[3] This paper investigates how well various different proxy measures capture long-run family income (which would be an ideal measure for universities to use were such sensitive data available). In doing so, it serves as a basis to help universities, practitioners and policymakers to decide what measures they should use in their contextual admission programmes.

While this brief focuses primarily on the use of measures for contextual admissions to university, many of the findings here will also apply to contextual recruitment, making this report of likely interest to employers as well as those working in higher education. It should however be noted that some of the issues discussed here, for example issues surrounding data access, will differ substantially between universities and employers, with discussion here primarily focused on barriers within HE.

METHODOLOGY

This report summarises the research of Jerrim (2020). This uses the Millennium Cohort Study (MCS) to investigate how well various proxies for family background – many used in contextual admissions and widening access schemes – correlate with long-run family income. Specifically, for 7,439 children in England who participated in this study, parents have reported their family income when the child was age 9 months, 3, 5, 7, 11 and 14. Information was also available on home postcode, meaning that various area-level proxy measures of socio-economic position (e.g. IMD, Acorn, POLAR) could be derived. Moreover, information is available on Free School Meal eligibility via links with children's school records. Together, this allows us to investigate how proxy measures of socio-economic status – of the type often used in contextual admissions – compare to a high-quality measure of long-run household income (as well as a multidimensional measure of family background, based upon parental education, occupation and household income). A selection of the proxy measures investigated by Jerrim (2020) can be found in Table 1 below.[4]

Table 1. Proxy measures of family background investigated in Jerrim 2020.

Measure	Level measured at
Index of Multiple Deprivation	LSOA
ACORN	Postcode
Free school meals	Individual
Income Deprivation Affecting Children	LSOA
Output Area Classification	LSOA
IFS socio-economic status index	Individual/Postcode
Young Participation by Area Rate / POLAR	MSOA
Tracking underrepresentation by area	MSOA
Transitory income (age 14)	Individual

This report examines how well each measure is correlated with long-run family income and long-run income-deprivation (defined as the bottom 20% of the long-run family income distribution). To give non-specialist readers an understanding the strength of association implied by such correlations, we describe those of 0.3 and below as "weak", those between 0.3 and 0.6 as "moderate" and those greater than 0.6 as "strong".

We also note the proportion of low-income pupils each measure is likely to miss when the socio-economic proxy measure is used 'optimally' (i.e. its 'false negative' rate), and the proportion of children each proxy classifies as 'disadvantaged' when they are not (i.e. its 'false positive' rate). This 'optimal' cut-point is determined empirically. It is the point used to define the disadvantaged group along the continuous proxy scale that minimises the aforementioned false negative and false positive rates (in identifying children who sit in the bottom 20% of the permanent income distribution).

Bias is also investigated for each proxy as a measure of permanent family income in terms of gender, ethnicity, single-parent households, whether living in London, home ownership and whether the child was born to a young mother (age under 21). Specifically, after controlling for the proxy measure, we consider whether there remains any difference in the probability of a child living in income deprivation by these demographic characteristics. If this is the case, then it suggests that the proxy does not fully capture differences in the economic circumstances of these groups. Finally, we also consider how well each proxy captures the academic achievement of disadvantaged pupils. In particular, we compare the proportion of 'disadvantaged' pupils who achieve the equivalent of the key 5 A*-C GCSE threshold according to each proxy measure, and how this compares to children from long-run low-income backgrounds.

The next section starts with a summary overview of results (Table 2), before going through each measure in more detail.

KEY FINDINGS FOR EACH MEASURE

Table 2. Summary comparison of the results for each proxy measure

Measure	Level	Correlation with permanent income	Correlation with permanent income deprivation	False negatives	False positives	Definition of proxy for poverty	Optimal cut-off	% achieving 5 A*-C (or equivalent)
IMD	LSOA	0.48 (moderate)	0.47 (moderate)	27%	30%	Bottom 20%	34%	37%
IDACI	LSOA	0.44 (moderate)	0.48 (moderate)	27%	32%	20%	37%	37%
FSM	Individual	0.44 (moderate)	0.68 (strong)	26%	20%	20%	33%	26%
POLAR	MSOA	0.38 (moderate)	0.22 (weak)	39%	48%	20%	54%	41%
TUNDRA	MSOA	0.30 (weak/ moderate)	0.17 (weak)	52%	42%	20%	49%	42%
ACORN	Postcode	0.54 (moderate)	0.56 (moderate)	24%	31%	49%	41%	41%
OAC	OA	0.41 (moderate)	0.46 (moderate)	27%	32%	38%	N/A	42%
IFS	Composite	0.55 (moderate)	0.51 (moderate)	21%	32%	20%	40%	34%
Single-year income	Individual	0.81 (strong)	0.73 (strong)	14%	21%	20%	34%	N/A

Notes: False positive/negatives based upon when "optimal" cut-off used (other than for the OAC). The "definition of proxy for poverty" is used for the % achieving 5 A*-C and correlation with permanent income deprivation figures. An experimental version of TUNDRA, based upon data at the lower super output area level, has recently been published, but not considered here. LSOA = Lower super output area; MSOA = Middle super output area; OA = Output area. The 'optimal' cut-point is determined empirically; it is the point used to define the disadvantaged group along the continuous proxy scale that minimises the false negative and false positive rates (in identifying children who sit in the bottom 20% of the permanent income distribution).

Index of Multiple Deprivation (IMD)

Correlation with income: **0.48 (moderate)**
False negatives: **27%**
False positives: **30%**

The IMD is the official measure of relative deprivation used in England. It is based upon seven indicators about the local area (approximately 650 households) in which a young person lives: income, employment, health, education, crime, housing and living environment. As an area-level measure, it requires information about home postcode, collected from schools, government records or self-reported by pupils. When used by universities in contextual admissions, disadvantaged pupils are usually defined as IMD quintiles 1 and 2 – the most disadvantaged 40% of children by this measure. This is broadly consistent with evidence that suggests the most disadvantaged 34% of pupils according to this measure serves as the best proxy for a low-income family background (Jerrim 2020).

The correlation between IMD and family income is moderate (Pearson correlation = 0.48), though with it being slightly better at predicting income affluence (correlation = 0.52) than income deprivation (correlation = 0.47). Even when used optimally, it can only capture income deprivation with limited accuracy, missing around 27% of children from low-income backgrounds. Moreover around 30% of children are inaccurately classified as coming from a disadvantaged (permanently 'low-income') background using the IMD.

There are also some important biases in this measure as a proxy for low family income. Specifically, the IMD underestimates the probability that BAME children, those living in London, those living in rented accommodation, single parent families and those children with young mothers are in the lowest income group. The IMD can nevertheless be used to accurately approximate educational achievement of disadvantaged pupils at an aggregate level; 34% of low-income children achieve five A*-C grades, compared to 37% of children in the bottom IMD quintile (IMD Q1).

Overall, the IMD has the advantage of being a widely used measure across multiple contexts (both within education and beyond), is freely available in the public domain and only requires information on young people's postcodes. A notable limitation, however, is that the IMD is not comparable across the four constituent countries that form the UK.[5] It is also only modestly correlated with family-income, failing to identify almost one-third of low-income children – particularly those who are BAME, live in a single-parent household and who rent their accommodation.

Given the lack of UK-comparability, the IMD is unlikely to be a suitable widening participation indicator for universities in England with a substantial intake of Welsh, Scottish or Northern Irish students. Otherwise, it is likely to be best suited to where a simple "look-up" of a student's postcode is needed, where no further child-specific information is available (such as parental background or Free School Meal eligibility) and where there needs to be no cost attached.

Index of Deprivation Affecting Children Index (IDACI)

The IDACI index is a sub-scale of the Index of Multiple Deprivation discussed above. It is based upon the proportion of 0-15-year-old children living in income deprived families within the child's local area (approximately 650 households). This is operationalised as families either in receipt of income support, income-based job-seekers allowance, income-based Employment and Support allowance, pension credit, universal credit, or in-receipt of working tax credit with an income below 60 percent of the national median.

It requires information about home postcode, collected from schools, government records or self-reported by pupils. To our knowledge, it has rarely been used as an individual indictor in contextual admissions or widening access schemes by universities, although it is now included within UCAS's Multiple Equality Measure),[6] and often mentioned in universities' widening access documents.[7] When it has been used, disadvantaged pupils are usually defined as those in IDACI quintiles 1 and 2 – the most disadvantaged 40% of children by this measure. This is broadly consistent with evidence that suggests the most disadvantaged 37% of pupils according to this measure serves as the best proxy for a low-income family background.

The correlation between IDACI and family income is moderate (Pearson correlation = 0.44), though with it being slightly better at predicting income affluence (correlation = 0.52) than income deprivation (correlation = 0.48). Even when used optimally, it can only capture income deprivation with limited accuracy, missing around 27% of children from low-income backgrounds. Moreover around 32% of children are inaccurately classified as coming from a 'low-income' background using IDACI.

Correlation with income: **0.44 (moderate)**
False negatives: **27%**
False positives: **32%**

There are also some important biases in this measure as a proxy for low family income. Specifically, the IDACI underestimates the probability that BAME children, those living in London, those living in rented accommodation, single parent families and those children with young mothers are in the lowest income group. The IDACI can nevertheless be used to accurately approximate educational achievement of disadvantaged groups at an aggregate level; 34% of low-income children achieve five A*-C grades, compared to 37% of children in the bottom IDACI quintile (IDACI Q1).

Overall, the IDACI has the advantage of being freely available in the public domain and only requires information on young people's postcodes. Its main limitations are the same as for the IMD (of which it is a subscale). Specifically, IDACI scores/ranks cannot be compared for students from different parts of the UK, fails to identify around one-third of low-income children, and underrepresents disadvantaged amongst BAME students, those living in single-parent households and who rent their accommodation (amongst other groups).

In summary, given the similarity between the IMD and IDACI indices, universities should only use one out of the two at most, and this should be consistent across all their outreach and admissions work. Given the more widespread use and understanding of the IMD across various fields, we suggest that this should be the preferred option out of the two.

Eligibility for Free School Meals (FSM)

Correlation with income: 0.44 (moderate)
False negatives: 26%
False positives: 20%

Eligibility for Free School Meals (FSM) is a widely used proxy for low-income used in academic research, policy and practice in England. It is information routinely recorded within the National Pupil Database (NPD) as part of the regular school census. FSM are a means-tested benefit, though the criteria used to determine eligibility for FSM has changed over time,[8] with the current guidelines for England, Northern Ireland, Scotland and Wales provided in Appendix A. With the introduction of Universal Credit, *"the government has said that it will offer FSMs to families in receipt of UC who have annual net earnings (i.e. after income tax and employee National Insurance) of £7,400 or less"*.[9] Moreover, importantly, children are flagged as 'eligible' for FSM in the NPD only if they are both eligible for and claiming FSM.[10] For instance, some families may not claim FSM due to a perception of there being a stigma associated with it. This will mean that FSM, as measured in the NPD, may miss some low-income pupils (those who are eligible for this entitlement, but do not claim it).

Information about FSM could be gathered from schools, via access to government administrative databases (i.e. the NPD) or by pupils (or their families) reporting this information. None of these approaches are problem free, either due to reporting/recall error, logistical problems with access to the data from schools or data-protection legalities if drawn from administrative data. As noted by the Office for Students (OfS; the UK higher education regulator) these challenges mean that universities do not typically have access to this information when making admission decisions.[11] As the basis for the official government measure of disadvantage in schools (i.e. through its link with eligibility for the Pupil Premium), the Sutton Trust has previously called for FSM data to be made available to universities.[12]

When using a single year of FSM data, 'disadvantage' is simply defined as those eligible for FSM, with 'advantaged' defined as those who are not. Consequently, around 17 percent of young people in this cohort are defined as disadvantaged according to this metric when FSM information is drawn from a single year (based upon our analysis of the MCS database). However, it is also possible to use information from across multiple school years to calculate the proportion of time children were eligible for FSM throughout their time at school. When doing so, we find it optimum to take the bottom third of this "proportion of FSM-eligible time at school" variable. Table 3 illustrates the percentage of time children spend at school being eligible for free school meals.

The correlation between FSM and family income is perhaps not as strong as many might suspect, even when one takes the proportion of time a child has been eligible for FSM throughout their time at school (Pearson correlation = 0.44). This, however, is due to the fact that it is a measure focused upon the lower part of the income distribution, and hence does not discriminate between middle and high-income families well. In other words, FSM is not good at distinguishing if a young person comes from a high or medium background, but is good at distinguishing high/medium income from low income households. This is illustrated by the fact that the correlation between the "proportion of time at school eligible for FSM" variable and income deprivation is actually quite strong (correlation = 0.69). Nevertheless, around one-in-five of low-income children will be missed using this measure, while around one-in-five will be incorrectly classified as coming from a low-income family. On the other hand, FSM has one of the lowest levels of bias out of all the contextual indicators considered. In particular, there is less bias against single parent households and renters (when proxying long-run low household income) when using FSM compared to other (mostly area-based) measures.

Overall, FSM eligibility has the advantage that it is one of the most strongly correlated contextual indicators with low family-income, and a less biased proxy (particularly with respect to renters and single parent households) than many of the alternatives. The main drawbacks are mainly pragmatic. In particular, universities would require access to information about FSM eligibility of applicants over a number of years. This could be feasibly achieved through routine sharing of government records (the National Pupil Database) with universities, but to date this has been found challenging.

Table 3. Percentage of time at school children spend being eligible for free school meals

% of time at school eligible for FSM	%
Never FSM eligible	70%
0-10% of time	4%
11-20% of time	3%
21-30% of time	3%
31-40% of time	2%
41-50% of time	2%
51-60% of time	2%
61-70% of time	2%
71-80% of time	2%
81-90% of time	2%
91-100% of time	7%

Source: Jerrim (2020: Table B3) Measuring socio-economic background using administrative data. What is the best proxy available?.

POLAR (Youth Participation Rate)

POLAR is an indicator of university participation by local area. It is a key measure used in contextual admission in UK higher education, and is the main indicator used by the Office for Students to monitor the progress universities are making to increase the number of disadvantaged young people progressing to higher education. Hence, although POLAR was not designed to make individual level decisions (e.g. in making contextual admission offers) its use as a monitoring device provides a clear incentive to universities to use it in this way.

POLAR is a measure that captures how likely young people are to participate in higher education, depending upon the area that they live. Specifically, the 'young participation rate' is first calculated as the number of 18/19-year-olds from a given area who enter higher education and divide this by the total number of 18/19-year-olds who live in that area. The area used is the Middle Super Output Area (MSOA) which contain around 7,500 individuals (across all ages). The 'POLAR' classification is simply a categorised version of the youth participation rate, which divides this index into five equal groups (quintiles). Note that Jerrim (2020) uses the youth participation rate in his analysis – the continuous indicator that underpins POLAR - rather than the POLAR quintiles per se.

Correlation with income: **0.38 (moderate)**
False negatives: **39%**
False positives: **48%**

POLAR requires information about pupils' home postcode, collected from schools, government records or self-reported by pupils. It is widely used in contextual admissions and widening access schemes by universities; 16 of the 25 high-tariff universities with data available used it as a contextual indicator in 2017. [13] Disadvantaged pupils are usually defined using this measure as POLAR quintiles 1 and 2 – the most disadvantaged 40% of children. This is notably lower than the research by Jerrim (2020) which suggests the most disadvantaged 54% of pupils according to this measure needs to be used to serve as the best proxy for a low-income family background. This is partly due to the very poor correlation between POLAR and financial disadvantage of families (see next paragraph for further details).

The correlation between POLAR and family income is moderate (Pearson correlation = 0.38), with it being better at predicting income affluence (correlation = 0.47) than income deprivation (correlation = 0.22). Even when used optimally it can only capture income deprivation with limited accuracy, missing around 39% of children from low-income backgrounds. Moreover 48% of children classified as "disadvantaged" using the POLAR/YPR classification are not from a low-income background.[14] Out of all the measures considered, it also contains the greatest biases in terms of capturing economic disadvantage. Specifically, the POLAR measure has a particularly large bias against BAME students, those living in London, those with young mothers and those who rent their home. POLAR also overestimates the educational achievement of disadvantaged groups (at an aggregate level), while also underestimating educational inequality. In particular, around 41% of children in the bottom POLAR quintile (POLAR Q1) achieve 5 A*-C grades, compared to 34% of low-income children.

Overall, POLAR has very few advantages. It is conceptually flawed as a measure of socio-economic disadvantage. It is very poorly correlated with low family-income. It is biased against key demographic groups, including BAME students. And, compared to other neighbourhood-level measures, is based upon data at a more aggregated level (middle super output area, rather than lower super output area or postcode). Despite its current widespread use by universities, and the support it receives from the regulator (the Office for Students), it is inappropriate to use as a contextual indicator for socio-economic disadvantage – particularly when there are many easily accessible, superior alternatives.

TUNDRA

TUNDRA is an indicator of university participation by local area. It is an experimental measure of educational disadvantage developed by the Office for Students. While POLAR divides the number of 18 year olds in an area by the number of 18 year olds from that area participating in HE, TUNDRA tracks individuals from 16 and links their Key Stage 4 data through to their participation in HE at 18-19. Specifically, it is the proportion of 16-year-olds from state schools who went on to higher education divided by the total number of 16-year-olds within a given area. Due to this linkage, TUNDRA only covers students at mainstream state funded schools, which addresses one of the criticisms of POLAR, that low participation of state school students in an area could be masked in areas where a high proportion of households send their children to private schools with better HE progression rates than the area at large.[15] The area used is the Middle Super Output Area (MSOA), which contain around 7,500 individuals (across all ages), although an experimental version using information at the Lower Super Output Area (LSOA) has recently been developed.[16] The 'TUNDRA' classification is simply a categorised version of this university participation rate, which divides this index into five equal groups (quintiles). Note that Jerrim (2020) uses the TUNDRA quintiles in his analysis (which is different to the treatment of POLAR, where the underlying continuous variable - the Youth Participation Rate – was used).

TUNDRA requires information about pupils' home postcode, collected from schools, government records or self-reported by pupils. One difference between POLAR and TUNDRA is that the former is available for the whole of the UK, while the latter is available for England only. As a recently published experimental measure, TUNDRA does not currently seem to be used widely by universities in contextual admissions. Our analysis suggests that taking the bottom half of the university participation rate (i.e. all of TUNDRA Q1, Q2 and half of TUNDRA Q3) serves as the best proxy for socio-economic disadvantage. This is partly due to the very weak correlation between this measure and financial disadvantage.

The correlation between TUNDRA and family income is weak/moderate (Pearson correlation = 0.30), with it being particularly poor at capturing income deprivation (correlation = 0.17). Even when used optimally it can only capture income deprivation with limited accuracy, missing 52% of children from socio-economically deprived backgrounds. Moreover, around 42% of children classified as "disadvantaged" using TUNDRA are not from a low-income background.[17] Like POLAR, it is also biased (in terms of capturing long-run economic disadvantage of families) against certain demographic groups. Specifically, TUNDRA has a particularly large bias against BAME students, those living in London, those with young mothers, those living in single parent households and those who rent their home. TUNDRA also overestimates the educational achievement of disadvantaged groups (at an aggregate level), while also underestimating educational inequality. In particular, around 42% of children in the bottom TUNDRA quintile (POLAR Q1) achieve 5 A*-C grades, compared to 34% of low-income children.

Thus, TUNDRA shares many of the unattractive features described for POLAR (see above for the multiple problems listed). It has few obvious attractions. Like POLAR, TUNDRA should not be used by universities or employers to inform contextual admissions or recruitment.

Correlation with income: **0.30 (weak/moderate)**
False negatives: **52%**
False positives: **42%**

ACORN

Acorn is a geodemographic classification system developed by CACI Limited. The data are proprietary, and must thus be paid for by employers and universities. The Acorn classification system combines information from the Land Registry, administrative data and commercial data to divide each postcode in the UK into one of six Acorn categories, 18 Acorn groups and 62 Acorn types (a 'pen-portrait' of each Acorn type is available from https://acorn.caci.co.uk/downloads/Acorn-User-guide.pdf). These 62 Acorn types are based upon a combination of information and data sources, such as house sales, house rentals, accommodation designed for elderly people, high rise social housing, other housing lists, care accommodation, student accommodation, information about residents, benefits claimants, census and lifestyle data.

ACORN requires information about pupils' home postcode, collected from schools, government records or self-reported by pupils. According to previous Sutton Trust research,[18] it is only used by a handful of universities in deciding contextual admissions (just three of the 25 high-tariff universities with data available used it as a contextual indicator in 2017). However, some universities seem to have recently added it to their pool of metrics, including Oxford[19] and St Andrews.[20] When it has been used, disadvantaged pupils are usually defined as Acorn groups 4 (financially stretched) and 5 (urban adversity). Interestingly, around half of young people in England fall into one of these two groups. In contrast, our analysis suggests that the "optimal" measure of disadvantage using Acorn would be to take Acorn Type 40 and above (this includes the whole "urban adversity" group, but only some of the "financially stretched" group) – encompassing around 41% of the population.

The correlation between Acorn and family income is moderate - though slightly stronger than for most other area level measures (Pearson correlation = 0.54), and with it being somewhat better at predicting income affluence (correlation = 0.66) than income deprivation (correlation = 0.56). Even when used optimally, it can only capture income deprivation with limited accuracy, missing around 24% of children from low-income backgrounds. Moreover around 31% of children are inaccurately classified as socio-economically disadvantaged using the Acorn. Compared to some other area level measures, it is a slightly less biased proxy for low-income with respect to some key demographic groups such as renters and those with young mothers.

Overall, Acorn is perhaps the best available area-level measure currently on offer. Its strengths are that it measures disadvantage at a very localised level (postcode-level – covering an average of around 15 households),[21] has been designed to be comparable across the UK and is reasonably well correlated with low-household income. These factors make it a more attractive option than widely-used alternatives, such as the IMD and (particularly) POLAR. Its main disadvantage is that, as a commercial indicator, it is not free to use. Moreover, the exact methodology behind how it is derived is somewhat opaque. There also remain some questions about how Acorn should be used – with current practice where half the population fall into the "disadvantaged" group (including the definition used by the university of Oxford) somewhat questionable.

Correlation with income: **0.54 (moderate)**
False negatives: **24%**
False positives: **31%**

OAC

The OAC (Output Area Classification) is a geodemographic classification system developed by the Office of National Statistics. The data are open source, with each census Output Area (which is comprised of around 125 households) being classified into one of eight OAC groups, 26 groups and 76 sub-groups. The OAC data are categorical – and not clearly ordinal. These groupings have been formed based upon the demographic structure (e.g. age, marital status, ethnicity), household composition, housing type (e.g. detached house, flats, property ownership), socio-economic (e.g. educational qualifications, car ownership) and employment situation (e.g. industry of occupation, percentage of people in employment) of the output area. Further details about how the groupings have been formed are available from the ONS (see Jerrim 2020 for further details).

The OAC requires information about pupils' home postcode, collected from schools, government records or self-reported by pupils. It has rarely been used by universities in contextual admissions; none of the 25 high-tariff universities with data available used it as a contextual indicator in 2017, according to the Sutton Trust.[22] However, it has recently been listed by the University of Cambridge as one of the indicators that they use,[23] defined as households in supergroup 8, groups 3a, 3b, 3c, 4b, 7a, 7b, 7c and sub-groups 4a1, 4a2, 4c2 and 6b3.[24] Using the University of Cambridge definition, around 38% of the population fall into the disadvantaged socio-economic group (see Jerrim 2020 for further details).

Correlation with income: **0.41 (moderate)**
False negatives: **27%**
False positives: **32%**

The correlation between the OAC and family income is moderate (Pearson correlation = 0.41), and notably lower than perhaps the most comparable alternative measure (Acorn). It is slightly better at predicting income affluence (correlation = 0.55) than income deprivation (correlation = 0.46). There are some important biases in this measure as a proxy for low-income background. Specifically, the OAC underestimates the probability that BAME children, those living in London, those living in rented accommodation, single parent families and those children with young mothers are in the lowest income group. It also significantly overestimates the educational achievement of disadvantaged groups (at an aggregate level), while also underestimating educational inequality. In particular, around 42% of disadvantaged children according to the OAC measure achieves 5 A*-C grades, compared to 34% of low-income children.

Overall, there seems little reason for universities and employers to use the OAC in their contextual admissions programmes. There are other widely used, open access area-level measures (such as the IMD) that are equally as good or better for this purpose. Moreover, if universities or employers are willing to pay, then Acorn may be a slightly better alternative. Thus, in summary, there are no standout strengths of the OAC that motivate its use in contextual admissions.

IFS composite indicator

The Institute for Fiscal Studies (IFS) measure of socio-economic status was first developed in a paper in 2013.[25] It has since been used in a relatively small number of academic papers.[26] It combines information from a number of the proxies detailed above, in particular FSM eligibility, the IMD, Acorn and a number of census variables. In its original carnation, the IFS socio-economic status index included the following information (a) eligibility for Free School Meals at age 16; (b) Index of Multiple Deprivation score; (c) Acorn type and (d) Neighbourhood socio-economic status, education level and housing tenure. These variables are combined into an index using a statistical technique known as a principle components analysis (see Jerrim 2020 for further details).

The IFS measure requires both information about young people's home postcode and data about their Free School Meal eligibility. Thus, pragmatically, it requires access to administrative government databases, such as the National Pupil Database. It has not been used thus far by any employer or university in contextual admissions, but it is becoming increasingly used in academic and social research. Our analysis reveals that the 'optimal' cut point to define disadvantage occurs at the 40th percentile of the IFS scale (i.e. approximately the bottom 40 percent of the population falls into the IFS scale disadvantaged group).

Correlation with income: **0.55 (moderate)**
False negatives: **21%**
False positives: **32%**

The correlation between the IFS measure and long-run family income is moderate - similar to the Acorn measure (Pearson correlation = 0.55 compared to 0.54 for Acorn), with it being slightly worse at predicting income deprivation (correlation = 0.51 compared to 0.56 for Acorn). Even when used optimally, it can only capture income deprivation with limited accuracy, missing around 21% of children from low-income backgrounds. Moreover around 32% of children are inaccurately classified as socio-economically disadvantaged using the IFS measure. It also performs similarly to Acorn in terms of the extent of bias against key demographic groups.

An interesting strength of the IFS measure is that it can accurately capture the achievement of disadvantaged groups – and the magnitude of socio-economic gaps in educational achievement – at an aggregate level. Specifically, 34% of low-income children achieve five A*-C grades, which is the same (34%) of children in the bottom IFS quintile (IFS Q1). Moreover, the work of Jerrim (2020) illustrates that the IFS measure can accurately proxy the income-educational achievement relationship across the whole spectrum of the income distribution.

In summary, the IFS measure is likely to be of limited use in contextual admissions. The added complexity of combining information on FSM eligibility, Acorn and census data does not seem to bring substantial benefits in identifying socio-economically disadvantaged students. The one potential exception, however, may be if contextual admission schemes start to target other socio-economic groups – such as those from "middle-income" backgrounds. Here, the detailed, continuous nature of the IFS measure may offer some advantages. However, outside of contextual admissions, the IFS measure should become more widely used in research using administrative data exploring the socio-economic inequalities in educational achievement.

Family income measured in a single year

Recently, calls have been made to give universities access to a "household-income dataset".[27] This would provide universities with data about the income background of young people, most likely for one particular financial year. This would clearly offer universities some hope in identifying low-income pupils, but would still not be problem free. Outside of the obvious data protection issues, income data from a single year can be "noisy", and may not accurately capture the long-run economic situation of a child's family. Moreover, income data can be incomplete, with particular challenges in accurately capturing the earnings of the self-employed. If such data are not available from government databases, self-reported information can be gathered from young people and their families, though this will clearly contain some degree of error. Despite these issues, in 2017 four out of the 25 high-tariff universities used low household income as a contextual indicator.[28]

Correlation with income: **0.81 (strong)**
False negatives: **14%**
False positives: **21%**

The correlation between family income from a single year and the long-term economic situation of a household is strong, though not perfect (Pearson correlation = 0.81). The correlation between single-year income and long-run economic deprivation is lower at 0.73. Importantly, this is similar to the correlation between long-run economic deprivation and the proportion of time young people were eligible for FSM during their time at school (0.69). Indeed, when used optimally, single-year income will continue to miss around 14% of children from long-term low-income households. It will also classify around 21% of children as coming from permanently low-income backgrounds when they are not.

Overall, although there are obvious attractions to allowing universities access to a household-income dataset, as suggested by the Russell Group, there are viable alternatives that are likely to be equally valuable in identifying low-income groups. Specifically, information on FSM-eligibility throughout young people's time at school provides broadly the same degree of classification accuracy as a single year of household income. Given the sensitive nature of sharing such a household-income dataset widely with universities, we suggest that providing universities with long-term information on FSM eligibility is a more practical alternative. The one exception – where more fine-grained information on household income would provide additional use – is if contextual admissions start to target other groups (e.g. middle-income families).

Parental education / "first-in-family"

Out of 24 Russell Group universities, 15 use whether a young person is the "first in family" to go to university as part of their widening participation criteria (see Table 4). Unfortunately, comparable information about this indicator – which is essentially a measure of whether either of a young person's parents holds a degree – was not reported by Jerrim (2020), whose work focused upon measures available using administrative data.

There has however been other recent work into the properties of parental education (and, in particular, whether either parent holds a degree) as a potential widening participation indicator[29] With previous research finding that *"about two-thirds of recent graduates are FiF [first-in-family]"*. In other words, most recent graduates from universities in England are the first in their family (excluding siblings) to do so.

Table 4 provides further information about this measure. In particular, it compares the characteristics of first-in-family graduates (i.e. neither of their parents not hold a degree) to those who are not the first-in-family to obtain a degree (i.e. at least one of their parents holds a degree). This illustrates how there are clear differences in affluence and broader measures of socio-economic background between the two groups. For instance, FiF graduates are much less likely to have a parent working in a higher managerial occupation (40% versus 85%), who own their own home (76% versus 92%) and were less likely to attend an independent school (4% versus 14%). They also, on average, took fewer A-Levels, were more likely to be eligible for FSM during their time from school, and less likely to be of white ethnicity. On the other hand, the first-in-family group is also clearly quite mixed in terms of parental education levels, with roughly a quarter falling within both the "higher education below degree" and "less than GCSE" categories. Nevertheless, overall, Table 4 does provide some support for parental education – and, in particular, whether either parent holds a degree – as a measure to be used in widening participation programmes.

Table 4. Properties of the first-in-family to attend university

	First-in-family graduates	Not first-in-family
Average number A-Levels	2.4	3.3
Parental education		
Degree	0%	100%
HE below degree	28%	0%
A-Level	23%	0%
GCSE A*-C	26%	0%
Below GCSE	23%	0%
Social Class		
Higher managerial	40%	85%
Intermediate	26%	6%
Routine / manual	24%	3%
Other	11%	6%
% homeowner	76%	92%
% independent school	4%	14%
% FSM eligible	10%	2%
% White	60%	73%

Source: Henderson, Shure and Adamecz-Voigyi (2019) First in family university graduates in England.

The issue that is likely to constrain information about parental education in contextual admissions is that it will typically be based upon young people's (or possibly their parents) reports, and is hard to independently validate. This is because there is no easy accessible administrative database capturing information about parental education, with the only practical way to access this to be to ask young people to provide such information. Yet this comes with obvious issues if it were to be used to make high-stakes decisions such as in contextual offers; it would provide a clear incentive for young people to misreport. This is in addition to the problem that they may genuinely not know their parents education level. Moreover, in the case of step-families, it may not be entirely clear whose education should be reported.

Together, this suggests that parental education is likely to be a useful indicator for lower-stakes widening participation activities (e.g. eligibility for certain types of outreach programmes). For higher-stakes activities – such as contextual offers – the fact it is difficult to independently verify makes it less preferable.

DISCUSSION AND CONCLUSIONS

Within universities across the United Kingdom, there has been much recent interest in the issue of widening participation and contextual admissions. With increasing attempts to increase higher education participation amongst historically underrepresented groups, there has been a need to identify those young people at whom higher education institutions should target their widening participation efforts. A challenge that has long been faced is that universities only have limited information available about young people's demographic and socio-economic background. Hence a range of proxy measures – many based upon young people's home address – have become widely used to identify potential participants for widening participation activities and in making contextual grade offers. Yet, despite their widespread use, relatively little is known about how well these proxy measures capture individual-level socio-economic position. For instance, is there one proxy measure that consistently stands out as a better measure of socio-economic status than the others, and hence that universities should always use? Or are there other potentially accessible measures not currently in use that could be a "game-changer" in how such systems operate?

This report has addressed such issues, investigating the properties of a number of measures that are (or could) be used by universities in setting widening participation and contextual admission criteria. I find that the number of years a child has been eligible for FSM during their time at school is the best available marker for living in childhood poverty. This is thus likely to be the most suitable – and pragmatic – choice of indicator that could be used for the purpose of contextual admissions by universities in the future. Until this information becomes available, an area-level proxy will need to suffice. The Acorn classification system is a leading candidate, though whichever measure is eventually decided upon, greater consistency across universities is needed. On the other hand, POLAR and TUNDRA are weak measures of socio-economic position, and should not be used by universities when making individual-level decisions (including in contextual admissions).

However, it is also important to recognise that there a number of other issues with several of the indicators covered in this report. First, many are neighbourhood-level indicators that rely upon young people postcodes. As noted by others,[30] there are opportunities to game the system with such measures, where the postcode of another family member could be used instead of whether the young person usually lives. This is also a problem for some other measures already currently used by universities, such as parental education, including whether a potential applicant is their first in their family to attend higher education. Second, the "best" indicators to use for contextual admissions require individual level data – either family-income or a closely-related proxy such as FSM-eligibility. Although sharing this information widely with universities is likely to raise some important data protection issues, getting higher-quality information about the long-run economic situation of families is critical for the targeting of widening access schemes to improve (including contextual admissions). Third, for many of the indicators available, there are challenges with cross-UK comparability. This is particularly true for many of the area-level indicators such as the IMD, but may also have implications for individual-level measures as well (e.g. to what extent is being an FSM-eligible child in London comparable to being an FSM-eligible child in Wales?).[31] Moreover, for individual-level indicators to be widely used, it would require data-sharing across the four countries that form the UK. Further research is also needed to better understand whether eligibility for FSM holds the same meaning within these different contexts.

One possible option for universities to use in their widening participation programmes – including contextual admissions – is a "basket" of indicators. In other words, instead of using just one measure (e.g. Acorn) a selection of indicators are used (e.g. Acorn and the IMD). There would be many possible ways to implement such an approach, but the most likely is for universities to define a potential applicant as "disadvantaged" if they fall into the most disadvantaged group for any of the indicators used. Such an approach would likely reduce the proportion of "false-negatives" (i.e. reducing the proportion of disadvantaged young people who do not get identified as disadvantaged by the measures), but at the cost of increasing the false-positive rate (i.e. more non-disadvantaged pupils get identified by the measure and thus become eligible for WP programmes). This trade-off thus becomes an empirical question, as to whether the benefits (reducing false-negatives) offsets the costs (increasing false-positives). But it also becomes a question for policymakers about the type of system we want in place; for instance, should universities widening participation efforts ensure that as many disadvantaged young people get offered additional opportunities, even if that means that more from middle-income backgrounds will get such extra support as well?

Finally, greater thought, discussion and evidence is needed on how each of the indicators are used. It has become popular for the bottom quintile (or bottom two quintiles) of many indices used to flag young people from disadvantaged backgrounds. Yet little explanation or evidence has been offered as to why such cut-offs have been chosen. This last point then leads to a bigger picture question around contextual admissions – who exactly do we want such schemes to help? It seems that an assumption implicitly made is that such schemes should be targeted at those from the most disadvantaged backgrounds. There are, however, arguments that the scope of such programmes should be broader – and potentially accessible to young people from middle-income backgrounds as well. For instance, more than 30% of Oxford's intake in 2019 attended an independent school (despite educating just 7% of the population). Against this backdrop, policymakers may wish to ask themselves whether targeting young people from both low and middle income households might be the best way to widening access to the UK's most sought after universities, in order to further promote social mobility.

RECOMMENDATIONS

1. To improve targeting to contextual admissions and widening access schemes, **universities and employers need further individual data about the socio-economic background of applicants, in particular Free School Meal eligibility.** The creation of a "household-income" database, as suggested by the Russell Group, would be beneficial, but is likely to be difficult to implement. As it is already collected in official datasets, we suggest that information on the proportion of time young people have been FSM-eligible throughout their time at school would be a valuable alternative.

2. **There should be greater transparency and consistency from universities and employers when communicating how contextual data is used.** If they are to take advantage of access measures, it is crucial that applicants are aware of if and how they may benefit from contextualisation. Universities and employers should publicise the criteria, including the measures used, clearly on their websites, along with how and when they are taken into account. The current situation – where different organisations use different indicators in different ways while not being transparent in their use – can lead to confusion.

3. **Universities and employers should prioritise use of the most robust measures for contextualised admissions and recruitment.** Where free school meals eligibility is not available, priority should be given to ACORN, the best area-level measure, followed by the Index of Multiple Deprivation (IMD). If a basket of measures is used, these most robust measures should be weighted most strongly.

4. **The POLAR and TUNDRA measures should not be used in contextual admissions for individual students.** While intended as a measure of HE under-representation, rather than socio-economic disadvantage, it can have a counter-productive impact on accurately identifying those suffering from socio-economic and educational disadvantage, and its use by universities in their widening access schemes, or as part of contextual admissions should be avoided.

5. **The Office for Students should review the role of POLAR and the inclusion of specific measures of socio-economic disadvantage in advance of the next round of Access and Participation Plans.** Despite the stated intentions of the OfS, the current emphasis on POLAR-based targets for widening participation incentivises a narrow focus on this measure by universities. When developing the next round of APP's, the OfS should consider explicitly including a specific measure of socio-economic disadvantage in targets alongside or instead of POLAR. Free School Meal eligibility, as the basis for the official government definition of disadvantage in schools, would be the natural candidate and would enable a more joined-up national policy approach across schools and HE.

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31. Note - See Appendix A for details of how FSM eligibility criteria vary across England, Northern Ireland, Scotland and Wales.

APPENDIX A. ELIGIBILITY CRITERIA FOR FREE SCHOOL MEALS ACROSS THE UK

England

- Income Support
- income-based Jobseeker's Allowance
- income-related Employment and Support Allowance
- support under Part VI of the Immigration and Asylum Act 1999
- the guaranteed element of Pension Credit
- Child Tax Credit (provided you're not also entitled to Working Tax Credit and have an annual gross income of no more than £16,190)
- Working Tax Credit run-on - paid for 4 weeks after you stop qualifying for Working Tax Credit
- Universal Credit - if you apply on or after 1 April 2018 your household income must be less than £7,400 a year (after tax and not including any benefits you get)

Scotland

- Universal Credit (where your monthly earned income is not more than £610)
- Income Support
- income-based Job Seeker's Allowance
- income-based Employment and Support Allowance
- support under Part VI of the Immigration and Asylum Act 1999

The child is also entitled to free school lunches if their parents get:

- Child Tax Credit, but not Working Tax Credit, and your income is less than £16,105
- both Child Tax Credit and Working Tax Credit and have an income of up to £7,330

Wales

- Income Support
- Income Based Jobseekers Allowance
- Support under Part VI of the Immigration and Asylum Act 1999
- Income-related Employment and Support Allowance
- Child Tax Credit, provided they are not entitled to Working Tax Credit and their annual income does not exceed £16,190. (HM Revenue and Customs are responsible for assessing the level of annual income.)
- Guarantee element of State Pension Credit.
- Working Tax Credit 'run-on' - the payment someone may receive for a further four weeks after they stop qualifying for Working Tax Credit.
- Universal Credit

Northern Ireland

- Income Support;
- Income Based Jobseeker's Allowance;
- Income Related Employment and Support Allowance;
- Guarantee Element of State Pension Credit;
- Child Tax Credit or Working Tax Credit with an annual taxable income of £16,190 or less;
- Universal credit and have net household earnings not exceeding £14,000 per year.

Or:-

- if you are an Asylum Seeker supported by the Home Office Asylum Support Assessment Team (ASAT); or
- if your child has a statement of special educational needs and is designated to require a special diet.