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Quants & Crits: using numbers for social justice (or, how not to be lied to with statistics)

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INTRODUCTION

A day after a black activist was kicked and punched by voters at a Donald Trump rally in Alabama, Trump tweeted an image packed with racially loaded and incorrect murder statistics ... None of the numbers are supported by official sources. The figures ... are wildly inaccurate. And, as several news organizations quickly noted, [the claimed source for the statistics] the ‘Crime Statistics Bureau’ doesn’t exist. (PolitiFact, 2015)

Numbers have a fascination for many people. Numbers are especially appealing to those in power when they appear to lend authoritative ‘scientific’ backing to a favoured stereotype. Sometimes the numbers can be easily discredited, as was the case with the entirely fictitious crime stats retweeted by a soon-to-be President of the USA. In that case the media used its resources to prove that the numbers were invented. Unfortunately, education statistics rarely face this level of wider scrutiny. Indeed, many ‘experts’ (policy-makers and academics) create and/or publicize figures that do not stand up to critical race-conscious scrutiny. A key problem is that many feel intimidated by numbers. When we encounter a news story, or a piece of research, that uses qualitative data (such as striking interview quotations) we know enough to question how the material was generated; e.g. what questions were interviewees asked? have the quotations been edited or taken out of context? These basic critical inquiries come naturally because, in everyday life, people are used to judging the trustworthiness of qualitative data – the kinds of thing heard at work, on the street, and in the news. But such questions do not come so easily when faced with numbers. Statistics are widely viewed as an authoritative, ‘factual’ source of information. Even when people have a gut-feeling that the numbers (or their interpretation) are not correct, many lack the skills to seriously explore and critique quantitative data. In this chapter we explore and apply a series of principles (first outlined in Gillborn, Warmington & Demack, 2018) to help guide a critical race-conscious use of statistics. We take inspiration from Darrell Huff’s slim volume ‘*How to Lie with Statistics*’ (first published in 1954). Described, in the journal *Statistical Science*, as ‘the most widely read statistics book in the history of the world’ (Steele, 2005), Huff’s enduring appeal is the ability to demystify statistics by looking at how the everyday use of numbers (especially in news media) can give a false impression of reality. In a similar spirit, guided by the defining characteristics of Critical Race Theory (CRT) (Delgado & Stefancic, 2017; Ladson-Billings & Tate, 1995; Matsuda, Lawrence, Delgado & Crenshaw, 1993; Taylor, Gillborn & Ladson-Billings, 2016), we offer a brief commentary on some common problems that are encountered when statistics are used in relation to race equity, social justice and education.

QUANTITATIVE CRITICAL RACE THEORY (QuantCrit): A WORKING GUIDE

We are by no means the first to set out ways in which critical scholars should think more carefully about how quantitative data might be used to frustrate and/or support the struggle for equity and social justice in education. We have sought to build upon previous work and develop the beginnings of a coherent CRT-inspired approach we call, for sake of simplicity, *QuantCrit*: both the name and the process was directly inspired by the ground-breaking work of scholars at the interface of CRT and Dis/ability Studies as they began to formulate the outline for Dis/ability Critical Race Theory (DisCrit) (cf. Annamma, Connor & Ferri, 2013; Connor, Ferri & Annamma, 2016). We view

QuantCrit as a framework to help take forward a critical-race methodology that takes seriously the potential of numbers to work in the service of equity and dismantle their frequent deployment in defence of White Supremacy and oppression. QuantCrit uses the core principles of CRT to provide a set of sensitizing ideas that can be applied to any situation where quantitative data is being (or could be) used in relation to a race-conscious analysis, project or argument. In the rest of this chapter we consider three of the five QuantCrit principles and illustrate them with a series of examples drawn from real world projects and problems. The examples are not exhaustive and several are relevant to more than one principle. The five QuantCrit principles can be briefly summarized as:

I. The centrality of racism - Racism is a complex, fluid and changing characteristic of society that is not automatically nor obviously amenable to statistical inquiry. In the absence of a critical race-conscious perspective, quantitative analyses tend to remake and legitimate existing race inequities.

II. Numbers are not neutral - QuantCrit exposes how quantitative data is often gathered and analyzed in ways that reflect the interests, assumptions and perceptions of White elites. One of the main tasks of QuantCrit, therefore, is to challenge the past and current ways in which quantitative research has served White Supremacy, e.g. by lending support to deficit theories without acknowledging alternative critical and radical interpretations; by removing racism from discussion by using tools, models and techniques that fail to take account of racism as a central factor in daily life; and by lending supposedly 'objective' support to Eurocentric and White Supremacist ideas.

III. Categories are not natural: for *race* read *racism* - QuantCrit interrogates the nature and consequences of the categories that are used within quantitative research. In particular, we must always remain sensitive to possibilities of 'categorical alignment' (Artiles, 2011; Epstein, 2007) where complex, historically situated and contested terms (like race and dis/ability) are normalized and mobilized as labeling, organizing and controlling devices in research and measurement. Where 'race' is associated with an unequal outcome it is likely to indicate the operation of racism but mainstream interpretations may erroneously impute 'race' as a cause in its own right, as if the minoritized group is inherently deficient somehow.

IV. Voice and Insight: data cannot 'speak for itself' - QuantCrit recognizes that data is open to numerous (and conflicting) interpretations and, therefore, assigns particular importance to the experiential knowledge of people of color and other 'outsider' groups (including those marginalized by assumptions around class, gender, sexuality, and dis/ability). QuantCrit seeks to foreground their insights, knowledge and understandings to inform research, analyses, and critique.

V. Social justice/equity orientation: a principled ambivalence to numbers - QuantCrit rejects false and self-serving notions of statistical research as value-free and politically neutral. CRT scholarship is oriented to support social justice goals and work to achieve equity, e.g. by critiquing official analyses that trade on deficit assumptions, and working with minoritized communities and activist groups to provide more insightful, sensitive and useful research that adds a quantitative dimension to anti-oppressive praxis.

The Centrality of Racism

CRT views 'race' as 'more than just a variable' (Dixson & Lynn, 2013, 3). This is not only a methodological statement, it is also a political understanding that is integral to CRT's view of the World. Social relationships are hugely complex and fluid; they do not easily translate into simple categories and effects that are easily quantified.

Placing race at the center is less easy than one might expect, for one must do this with due recognition of its complexity. Race is not a stable category ... 'It' is not a thing, a reified object that can be measured as if it were a simple biological entity. Race is a *construction*, a set of fully social *relationships*.' (Apple, 2001, 204 original emphasis)

It follows that every attempt to 'measure' the social (especially in relation to 'race') can only offer a crude approximation of reality. We noted earlier that quantitative data are frequently assumed to be more trustworthy and robust than qualitative evidence; but this is turned on its head if we take seriously the *social* character of 'race'. Even the most basic numbers in relation to racial justice are open to multiple and profound threats to their meaning and use. In view of these problems (and the societal dominance of perspectives that are shaped by the interests, perceptions and assumptions of White people) *the most sensible starting point in any quantitative analysis is to interrogate the collection, analysis and representation of statistical material for likely bias in favor of White supremacy and the racial status quo.*

Don't accept numbers on trust. Ever.

Our first advice on dealing with statistics may seem glaringly obvious but experience suggests that numbers are rarely subjected to serious scrutiny; sometimes even the most cursory checks are not carried out by readers. For decades the debate about race and educational achievement has been one of the most controversial areas of research on both sides of the Atlantic (Gillborn, Demack, Rollock & Warmington, 2017). In the UK a landmark study was published in the early 1980s which included the first ever cross-tabulation for achievement in relation to both race *and* social class simultaneously (Craft & Craft, 1983). The research showed that Black students had lower average attainment than their White counterparts regardless of class background. The research was cited frequently and a key table, setting out the findings, was reproduced *in full* in numerous publications, including an official government inquiry into the educational attainment of minoritized students (Swann, 1985, 60). And yet the various columns in the table do not add up. In one of the columns, summarizing the results, there is a discrepancy between the constituent values and the 'total' given at the end² (Gillborn, 1990, 125). The discrepancy is relatively small but its constant repetition without query is significant: although the table had been reprinted numerous times, it seems no-one had bothered to check even that the table was internally consistent (let alone that the decisions about how to measure achievement and social class made sense).

Numbers are not color-blind

Statistics do not simply lie around waiting for interested citizens to pick them up and use them. *Numbers are no more obvious, neutral and factual than any other form of data.* Statistics are socially constructed in exactly the same way as interview data and survey returns, i.e. through a design process that includes, for example, decisions about which issues should (and should not) be researched, what kinds of question should be asked, how information is to be analysed, and which findings should be shared publicly. Even given the very best intentions (and there is no guarantee that everyone involved is well-intentioned) at every stage there is the possibility for decisions to be taken that obscure or misrepresent issues that could be vital to those concerned with social justice. This point is well illustrated by two examples separated by an ocean and almost 30 years:

England: 1988

St. George's Hospital Medical School has been found guilty by the Commission for Racial Equality of practising racial and sexual discrimination in its admissions policy ... a computer program used in the initial screening of applicants for places at the school unfairly discriminated against women and people with non-European sounding names... By 1988 all initial selection was being done by computer ... Women and those from racial minorities had a reduced chance of being interviewed independent of academic considerations. (Lowry & Macpherson, 1988)

United States: 2016

...judges, police forces and parole officers across the US are now using a computer program to decide whether a criminal defendant is likely to reoffend or not. The basic idea is that an algorithm is likely to be more 'objective' and consistent than the more subjective judgment of human officials ... But guess what? The algorithm is not colour blind. Black defendants who did not reoffend over a two-year period were nearly twice as likely to be misclassified as

higher risk compared with their white counterparts; white defendants who reoffended within the next two years had been mistakenly labelled low risk almost twice as often as black reoffenders. (Naughton, 2016)

These quotations describe how calculations made by computers, assumed by definition to be objective and free from human bias, not only reflected existing racist stereotypes but then acted upon those stereotypes to create yet further racial injustice. The news coverage generated by the events is strikingly similar. In both cases there was a sense of amazement that computer calculations could make such gross and racially patterned errors. In the US example the reporters who found the problem note that ‘even when controlling for prior crimes, future recidivism, age, and gender, black defendants were 77 percent more likely to be assigned higher risk scores than white defendants’ (Larson, Mattu, Kirchner & Angwin, 2016). A UK newstory was entitled ‘*Even algorithms* are biased against black men’ (Naughton, 2016 emphasis added). The surprise that accompanies such findings reflects a central problem that critical scholars encounter when they use, or are confronted by, quantitative data and processes. We argue that, far from being surprised that quantitative calculations can re-produce human bias and racist stereotypes, such patterns are entirely predictable and should lead us to treat quantitative analyses with at least as much caution as when considering qualitative research and its findings. Computer programs, the ‘models’ that they run, and the calculations that they perform, are all the product of human labour. Simply because the mechanics of an analysis are performed by a machine does not mean that any biases are automatically stripped from the calculations. On the contrary, not only can computer-generated quantitative analyses embody human biases, such as racism, they also represent the added danger that their assumed objectivity can give the biases enhanced respectability and persuasiveness. Contrary to popular belief, and the assertions of many quantitative researchers, numbers are neither objective nor color-blind.

Voice and Insight: data cannot ‘speak for itself’

As we have already noted, numbers are social constructs and, therefore, likely to embody the dominant (racist) assumptions that shape contemporary society. At every stage in the production of statistics there is the opportunity for racialized assumptions to come into play. Consequently, in many cases, numbers speak for White racial interests; their presentation as objective and factual merely adds to the danger of racist stereotyping where uncritical taken-for-granted understandings lay at the heart of analyses. Some of the most important ways in which White interests and assumptions play out in quantitative research is through the questions that are asked and the analyses that produce the answers.

Asking the ‘right’ questions

‘It is a scandal that ethnic minority kids are more likely to go to university than poor white ones’ – so read the headline in *The Telegraph*, one of the UK’s leading daily newspapers (Kirkup, 2015). The story reported official data showing that young people categorized as White British were less likely to attend university than their peers in most minoritized ethnic groups. The story echoes, and adds to, a familiar trope in British popular news reports which, for more than a decade, have systematically encouraged a myth of White racial victimization (see Gillborn, 2010a). The report focused on the overall percentage of young people in each ethnic group that were attending university. The focus on access to higher education as a whole helps to sustain an image of White disadvantage which disappears if we focus on access to elite institutions (that carry most weight in the field and the job market) and when minoritized groups are disaggregated in the analysis. For example, compared with their White counterparts, Black young people in Britain are more likely to attend university overall, but they are significantly less likely to attend a research-intensive high-status institution (Gillborn et al., 2018). In addition to querying the question that is being asked, therefore, critical scholars should also think about which questions are *not* being asked. For example, education research frequently focuses on achievement, and yet none of the press coverage about access to higher education asked about possible differences in *outcome* at the end of university. In answer to this question we offer Table 1 showing the proportion of each main ethnic group attaining the different classes of degree available at the end of undergraduate study; ranging from the very best result (a first class degree) through to a ‘third’ or ‘pass’ degree classification. *White students are more likely to gain a ‘First’ than any other group* (22.4%); Black students are the least likely to be awarded first class degrees (8.7% of Black students overall). This means that the odds of White undergraduates achieving the highest degree classification are around three times higher than their Black peers³. This is a significant race inequity

but, perhaps because the beneficiaries are White, it went entirely unremarked in the press furore about the overall access statistics.

Table 1 about here

When ‘models’ replace reality: the hidden danger of regression analyses

Quantitative analyses that claim to control for the separate influence of different factors are especially prone to misunderstanding and misrepresentation. Such ‘*regression*’ analyses rely on statistical models that are complex and often only partially explained in published accounts. Nevertheless, the results are generally reported as if they describe the real world rather than being a product of statistical manipulations. Regression analyses can turn reality on its head. For example, Gillborn (2010b: 261-3) describes a prominent research study (Strand, 2007) in which several minoritized groups were found to be less likely to gain access to a higher level of teaching and assessment. However, the researcher performed a regression analysis that claimed to control for the separate influence of numerous factors (such as maternal education, eligibility for free school meals and prior attainment): see table 2.

Table 2 about here

The table shows the likelihood of students being placed in the higher ‘tier’ for mathematics exams – this is important because the highest pass grades are only available to these students. The data is presented as odds ratios that compare the minoritized students’ chances of access to those of their White peers: odds that are higher than 1 show minoritized students as *more* likely to gain access, but a value *less* than 1 signals that they are less likely. The table lists values for several ethnic groups according to three calculations, presented in three columns. The original researcher labelled the first column the ‘base model’ but we prefer the term ‘reality’, since these values are generated by the distribution of the students in the real world. The distribution of students in the top tier signaled a significant under-representation for those who classified their ethnic identity as Black Caribbean (0.44), Pakistani (0.55), Black African (0.62) and Bangladeshi (0.65) heritage. In the table we have boxed these values to help them stand out. In the second and third columns the researcher performed regression analyses that try to build in (‘model’) the results that would have been predicted based on the performance of students with certain other identities (including their prior attainment earlier in their school careers, whether they receive free meals, their mothers’ education etc.). Each calculation adjusts the results and creates more cases of apparent *over*-representation (which we have signaled by an oval around the relevant value). The effect is dramatic; a situation that showed an under-representation of four out of five minoritized groups has now become a pattern claiming to reveal an over-representation of four of the five groups. By applying a statistical model (which assumes that poverty, income, maternal education and other ‘family’ characteristics are entirely unrelated to race/racism) the statistician has turned under-representation (minority disadvantage) into over-representation (White disadvantage).

A social justice/equity orientation: principled ambivalence to numbers

There is no inherent reason why critical race theorists should dispense with quantitative approaches entirely but they should adopt a position of *principled ambivalence*, neither rejecting numbers out of hand nor falling into the trap of imagining that numeric data have any kind of enhanced status or value. This is a stance that anti-racist scholars and activists have long practiced, for example, when they contest supposedly scientific claims about the biological nature of race - sometimes by invoking what science tells us about the unscientific status of race (Warmington, 2009; 2014). Critical race theorists work simultaneously *with* and *against* race, i.e. we know that race only exists as a social construct, but we recognize the sometimes murderous power of the fiction and seek to engage, resist and ultimately destroy race/racism. Similarly, QuantCrit should work *with* and *against* numbers by engaging with statistics as a fully social aspect of how race/racism is constantly made and legitimated in society.

Comparing ‘like-with-like’

a social justice orientation requires researchers to be sensitive to ways in which racism might operate through the everyday assumptions and processes of education. This is especially challenging in relation to quantitative research because most quantitative analyses are not informed by a critical understanding of social relations, let alone a CRT perspective on racism’s complex and fluid character. Racism does not operate separately to factors such as prior attainment, income, and parental education: racism

operates *through* and *between* many of these factors simultaneously. Quantitative research sometimes claims to disentangle these elements (e.g. by using regression analyses) and assumes that numerous factors (such as prior attainment, socio-economic status and parental education) are entirely independent of racist influences. Worse still, they treat inequalities in those indicators as if they are a sign of internal *deficit* on the part of the minoritized group rather than a socially constituted *injustice*. The use of 'prior attainment' scores is a particularly important example of this. Quantitative researchers frequently use students' test results at an earlier stage of their education as a way to group people of similar 'ability' (a maneuver that they claim compares 'like-with-like') but this erases racism and blames the students:

the racism that the kids experience on a daily basis [in ranked teaching groups, with restricted curricula and less-experienced teachers] translates into lower scores ... But those scores are then used to gauge "ability" and "prior attainment" ... the differences in prior attainment are treated as if they were deficits in the students themselves and nothing to do with their schools (Gillborn, 2010b, 266)

CONCLUSION

Bill O'Reilly: "You tweeted out that whites killed by blacks, these were statistics you picked up from somewhere, at a rate of 81 percent. And that's totally wrong. Whites killed by blacks is 15 percent, yet you tweeted it was 81 percent."

Donald Trump: "Bill, I didn't tweet, I retweeted somebody that was supposedly an expert (...) Bill, am I gonna check every statistic? I get millions and millions of people, @RealDonaldTrump, by the way. (...) this was a retweet. Bill, I'm sure you're looking out for me, everybody is. This was a retweet. And it comes from sources that are very credible, what can I tell you." (Farley, 2015)

Donald Trump's 2015 retweet of entirely false and racist 'crime statistics' is instructive. Trump was not the only person to gleefully share the graphic, which appears to have originated on a Nazi sympathizer's account (Johnson, 2015). We tend to subject numbers to relatively little scrutiny, especially when they align with our beliefs. Of course, one might expect politicians, policy-makers and academics to be more circumspect in their behaviour but, as we have shown in multiple examples above, this is often far from the case. We do not imagine that QuantCrit will spell the end of racist and misleading quantitative material in educational research. As critical race theorists we know that such changes are a matter of interest convergence and public protest, not a question of technical accuracy and reason. Nevertheless, we hope that the QuantCrit principles, and the examples we have set out above, will go some way to supporting greater critical scrutiny of quantitative data and the potential to harness its status in the cause of social justice.

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Notes

¹ All authors have contributed equally to this chapter.

² The original table gives the total number of 'middle class' respondents as 761 but this is six more than the figure that is produced by adding together the constituent values for middle class students elsewhere in the table.

³ This is based on the 'odds ratio' (also known as 'cross-product ratio') calculated by comparing the odds of success for White students compared with the odds of success for Black students (see Connolly, 2007, 107-8).