A Set-Analytic Approach to Intersectionality*

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In press, *Social Science Research*

*The authors would like to acknowledge the helpful comments of seminar participants at the University of Alberta, the University of Southern California, and the Swiss Federal Institute of Technology in Zurich.

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Abstract

In this paper, we propose a set-analytic approach to the study of intersectionality. Our approach builds on the intersectional view that combinations of attributes, such as *black females*, should be understood as qualitatively distinct states, not reducible to their component attributes. We show that interaction-based, quantitative approaches are not only inconsistent with the core assumptions of intersectionality but also may underestimate the presence of penalties linked to multi-category memberships. In contrast, we show that truth table analysis, a core feature of Qualitative Comparative Analysis, directly implements several of the core methodological concerns of the intersectionality perspective. The truth table approach offers two important advantages. (1) It provides a foundation for the comparison of logically 'adjacent' configurations—combinations of case characteristics that differ by only a single attribute. (2) It can accommodate case attributes that vary by level or degree in a set-theoretic, intersectional framework.

INTRODUCTION

Social categories profoundly shape both the formation and the experience of inequality. Accordingly, a significant body of research has examined how memberships in social categories affect life outcomes such as educational attainment, earnings, poverty, employment, divorce, imprisonment, and so forth (e.g., Browne and Misra 2003; Furstenberg 2007; Leicht 2008). In recent years the focus of this research has shifted from assessing the independent effects of social categories such as class versus race towards understanding the effect of combinations of category memberships. In particular, researchers using the concept of intersectionality have emphasized that social categories do not merely have independent effects on life chances, but that each combination of categories may constitute a qualitatively distinct state (e.g., Collins 2000, 2015; Crenshaw 1989, 1991; Hancock 2007a). According to the intersectionality perspective, a black female for instance should be viewed as a specific intersection of attributes—black *and* female—and not through the lens of the two traits, race, and gender, considered separately. Consequently, a key principle of the intersectionality perspective is that a single difference between two otherwise identical combinations of characteristics (e.g., a difference in race, gender, class, or sexual orientation) may constitute a qualitative difference between the two combinations of attributes. In other words, two individuals may be worlds apart even though they differ by only one relevant characteristic.

Empirically, the majority of studies within the intersectionality perspective have employed qualitative methods to study multi-attribute inequality (Hunting 2014), often drawing on interview data (e.g., Harvey 2005; Lui 2016; Meyer 2012), ethnographic fieldwork and participant observation (e.g., Contreras 2018; McQueeney 2009), as well as semiotic approaches from cultural studies (e.g., Gill 2009). A smaller number of studies have used mixed methods or quantitative approaches, usually examining differences in demographic groups by means of standard correlational analysis using additive and multiplicative approaches (e.g., Dubrow 2010; Logan 2010; Pedulla 2018). Here, the additive model often serves as a baseline, while the multiplicative interaction term accounts for the conditional effects of intersecting categories on an outcome of interest (Rouhani 2014). Other approaches have included the use of dummy variables (e.g., Brown 2018) or the analysis of separate subgroups based on their intersecting attributes (e.g., Harnois, 2005; Vespa 2009).

While each of these approaches offers particular advantages in terms of the insights they offer and the type of intersectional effects they are able to detect, each also has drawbacks. For instance, while qualitative approaches allow the researcher to capture the depth and richness of lived experience, they are not well-suited for detecting patterns of disadvantage across aggregated populations. Similarly, while conventional correlational approaches can show the pervasiveness of intersectionality across time (e.g., Mandel and Semyonov 2016), the interaction-based approach in particular has been criticized for not being able to capture the core argument that the intersection of two social categories may present a qualitatively different state (e.g., Hancock 2013; 2016).

In this paper, we offer an alternative to these prior paths by proposing a set-analytic approach to the study of intersectionality. Our approach directly builds on intersectionality's fundamental insight that combinations of characteristics, such as black females, should be understood as qualitatively distinct states, not reducible to their component categories. Indeed, instead of seeing black females as a specific cell in the cross-tabulation of two variables—race (black/white) and gender (male/female)—black females should be viewed as one of the four qualitatively distinct categories that constitute a single nominal-scale race•gender variable (black females, black males, white females, and white males).[1] Intersectional research on a three-way combination—for example, lesbian black females—entails conceptualization of a single nominal-scale variable (sexual_orientation•race•gender) with eight qualitatively distinct categories, from

[1] We use the mid-level dot to indicate intersectional conditions.

lesbian black females to straight white males. Each newly compounded dichotomous attribute doubles the number of qualitatively distinct combinations that are collectively operationalized as a single nominal-scale variable.[2]

Our set-analytic approach treats designated case attributes, such as race and gender, as *intersectional conditions*, a special category of attributes that demarcate salient subsets of cases. For example, researchers interested in the intersectionality of race and gender with respect to the causal conditions linked to poverty would divide their data set into as many race•gender combinations as are relevant to the analysis. In this example, race and gender are the designated intersectional conditions; they define overarching contexts for the analysis of poverty rates as well as the analysis of causal variables linked to poverty. We consider the *intersectional conditions* label a flexible designation reflecting researcher interest. Thus, our approach is agnostic with respect to the conditions that researchers designate as intersectional.

In the following we begin by outlining what for our purposes are the defining features of an intersectional approach, along with reviewing previous methods used to examine intersectionality empirically. We show that interaction-based, quantitative approaches in particular are not well aligned with the core insight of the intersectionality perspective. Using data from the National Longitudinal Survey of Youth, we demonstrate how our set-analytic approach is able to identify penalties stemming from intersectionality. We focus specifically on the assessment of 'extra' penalties, the idea that individuals who combine two or more disadvantaged social attributes experience penalties beyond those stemming from the effects of the disadvantages considered separately. Our overarching goal is to offer a toolkit that is both theoretically and empirically suited

[2] For the sake of simplifying the presentation, we use dichotomous attributes; our argument extends without alteration to combinations of multichotomous attributes.

to quantitatively studying intersectionality in a systematic manner and to open up new and different perspectives for the empirical analysis of memberships in social categories.

THE INTERSECTIONALITY PERSPECTIVE

Research employing the intersectionality perspective has expanded rapidly since its emergence in the late 1980s, both in terms of academic fields and geographic scope. Within this work, Hancock (2016:7) distinguishes three "sets of engagements" in intersectionality studies: applications of an intersectional framework, debates about intersectionality as a theoretical paradigm, and political activism that emerges from and uses an intersectional perspective. What is common to these three sets of engagement, however, is "the assertion that social identity categories such as race, gender, class, sexuality, and ability are interconnected and operate simultaneously to produce experiences of both privilege and marginalization" (Smooth 2013:11). As a way of capturing the complexity of social experience, intersectionality emphasizes that "events and conditions of social and political life and the self can seldom be understood as shaped by one factor. They are generally shaped by many factors in diverse and mutually influencing ways" (Collins and Bilge 2016: 2).

By emphasizing complexity and relatedness, the notion of intersectionality suggests that there is not one single axis of social division, but that there are many axes that combine and influence each other. Furthermore, research inspired by the intersectionality perspective is fundamentally comparative (Hancock 2013), as it addresses the experiences of different social groups by locating them in a categorical property space (McCall 2005). Each intersection of social attributes presents a qualitatively different state associated with a very different kind of experience with regard to life outcomes such as access to education and employment, exposure to discrimination, poverty, and so forth.

To illustrate a key insight of intersectionality, it is helpful to revisit one of the canonical examples of discrimination discussed by Crenshaw (1989), the court case *DeGraffenreid v. General Motors*. In this lawsuit from 1976, Emma DeGraffenreid and four other black women sued General Motors for discrimination based on race and gender. Specifically, the women claimed that General Motor's seniority system and 'last hired-first fired' personnel policy perpetuated the effect of past race and sex discrimination (DeGraffenreid v. General Motors 1976). As the court's decision noted, GM had hired only one black female before 1970, employed as a janitor. The firm did employ 155 black women in 1973, representing about 0.2 percent of the total GM employees in St. Louis (despite the fact that black women accounted for about 22 percent of the city's population). All these black women except the janitor lost their jobs in mass layoffs of 1974 because their hire dates were after May 24, 1968. In short, black women were disproportionally affected by GM's hiring and layoff policies.

What makes this case particularly relevant from an intersectionality perspective is that the disadvantage claimed by the five women stemmed from the *combination* of gender and race. GM asserted that it did not discriminate based on gender as the firm had hired female employees. The court rejected the plaintiff's argument of gender discrimination because not all women were discriminated against and suggested that the women consolidate their case with another one, *Nathaniel Mosley, et al., v. General Motors Corporation, et al.,* which was pending at the time. Most importantly, however, the court argued against the creation of ". . . a new classification of 'black women' who would have greater standing than, for example, a black male. The prospect of the creation of new classes of protected minorities, governed only by the mathematical principles of permutation and combination, clearly raises the prospect of opening the hackneyed Pandora's Box" (DeGraffenreid v. General Motors, 1976: 145).

Crenshaw (1989) used this case along with the concept of intersectionality as a powerful way to shed light on such situations where the experience of black women fell between the cracks of gender and race (and their associated discrimination). There is, however, another methodological implication of importance here. Specifically, the court rejected the intersectional argument that the experiences of black women were of a different quality, at least partly to avoid having to deal with the complexity that emerges when a property space doubles in size with the addition of each attribute. We return to this issue when we address its implications for the empirical assessment of intersectionality. For now, the key point is that the intersectionality perspective emphasizes that those at the intersection of social categories not only experience the effect of disadvantages in a cumulative manner (such as the disadvantage of being black plus the disadvantage being female, in this example), but that the intersection indicates a qualitatively different state where these disadvantages reinforce each other, leading to an 'extra penalty' where "one plus one equals three" instead of two. Theoretically, this 'extra penalty' is rooted in the interconnection of systems of power and domination as they relate to gender, race, and class, with systems of advantages and disadvantages powerfully shaping social inequality by acting in a mutually reinforcing manner (e.g., Lin and Harris 2010).

EMPIRICAL APPROACHES TO INTERSECTIONALITY

The fact that social inequalities coincide and reinforce has direct methodological implications, as variables that characterize the positions of individuals in social hierarchies tend to coincide, sometimes very strongly (e.g., Ragin and Fiss 2017). Methodological choices matter greatly because they determine what 'counts' as intersectionality (Collins and Bilge 2016) and whether we are able to detect and document the differences that emerge from multi-attribute memberships.

As noted previously, the majority of studies using the intersectionality perspective have employed qualitative methods to study the experience of multidimensional inequality across a variety of settings (e.g., Harvey 2005; Morris 2007; Gill 2009; McQueeney 2009; Cronin and King 2010;

Meyer 2012; Lui 2016; Amundson and Zajicek 2018; Contreiras 2018). The advantage of qualitative studies is their ability to directly assess and document the experience especially of discrimination emerging from the intersection of social categories. Part of intersectionality's appeal stems from its emphasis on flexibility in how identities are managed (Valentine 2007), rendering qualitative approaches such as ethnography, interviews, case studies, and the analysis of life histories particularly attractive and appropriate (e.g., Christensen and Jensen 2012).

While qualitative methods are thus highly compatible with the goals of intersectional research and provide powerful tools for understanding the complexity of individual and collective identities, a smaller number of studies have used quantitative approaches to trace the effects of intersectionality across large populations of cases. Rather than identifying mechanisms and processes, the fundamental goal of these studies has been to document patterns of intersectionality across different groups (e.g., Choo and Ferree 2010; Penner and Saperstein 2013).

To illustrate the quantitative approach to intersectionality, consider the core insight of the intersectionality literature that certain combinations of attributes carry 'extra' burdens or penalties. For example, black females have an especially high rate of poverty. Other combinations have other penalties, restrictions, or limitations. It is important for researchers to document these penalties, which in turn requires an agreed upon methodology for identifying 'extra' penalties.

[Table 1 about here.]

Table 1 shows hypothetical poverty rates for four race•gender categories—black females, black males, white females, and white males. In this example, black females have the highest rate of poverty, which provides basic descriptive evidence supporting the argument that they suffer an extra penalty when it comes to poverty. It is sometimes possible to use external criteria to define 'extra' when making these assessments. For example, a policymaker might assert that poverty rates in excess of 0.25 are 'unacceptable.' The rate for black females would be assessed as 'too high' using this external standard as a benchmark. This assessment could be embellished further with a statistical test of the significance of the difference between the observed black female poverty rate (.30) and the externally sourced benchmark rate (.25).

Another external criterion is the "four-fifths rule," set forth in the *Uniform Guidelines on Employee Selection Procedures* (U.S. Equal Employment Opportunity Commission, Civil Service Commission, Department of Labor, and Department of Justice, 1978). This rule asserts that *success rate* for a disadvantaged group in achieving a valued outcome should not be less than four-fifths (80%) of the rate of an advantaged group. The four-fifths rule is commonly used as a warning flag to signal possible adverse impact. Using the hypothetical data in table 1, the not-in-poverty rate for white males is 0.90; the not-in-poverty rate for black females is 0.70; 0.70 divided by 0.90 is 0.778 (77.8%). Thus, the argument that black females are saddled with an 'extra' penalty is supported when the four-fifths rule is applied to the data in table 1. Note that the four-fifths rule is not subject to the influence of sample size, which often has a determining impact on the results of significance tests (Hauenstein et al. 2013).

Other rubrics for defining 'extra' penalties are possible when externally derived benchmarks or rules are lacking. For example, it is possible to assess the statistical significance of the difference between the poverty rate for black females (.30) and the poverty rate registered by the most favored group, white males (.10). A more conservative comparison would be to assess the significance of the difference between the black female poverty rate and the second highest category, which in this example is the rate for black males (.20, which is tied for second place with the white female rate). A significant difference in the expected direction would provide support for the argument that black females confront an extra penalty when it comes to poverty.

While descriptively sound, some social scientists would not be convinced by the demonstrations just offered. The key concern is the definition of 'extra' penalty. For example, it is possible to argue that the black female poverty rate in table 1 offers no evidence of an extra penalty. Consider: the difference between the white male rate and the white female rate is 0.20 – 0.10 = 0.10, which yields a 10-point penalty for being female. Likewise, the difference between the white male rate and the black male rate is 0.20 – 0.10 = 0.10, which yields a 10-point penalty for being black. Taken together, these two differences indicate an 'expected' black female rate of 0.30, which is the white male rate plus the penalty for being female, among whites, plus the penalty for being black, among males. The observed black female rate of 0.30 is the same as this 'expected' rate, which undercuts the argument that black females endure an especially heavy penalty. According to the reasoning just presented, the observed black female poverty rate must be greater than 0.30 before the 'extra penalty' argument plausibly can be put forward.

While the calculation of an 'expected' rate based on observed differences (gender differences among whites and racial differences among males) may constitute a rigorous alternative to previous ways of defining 'extra', the calculation of an expected rate, as just described, is in fact at odds with core principles of intersectionality. The 'expected' black female poverty rate assumes a generic race effect and a generic gender effect that work in an additive manner, which contradicts the idea that the combination of these attributes should be viewed as a qualitatively distinct state, where combining disadvantages leads to an 'extra penalty.' From an intersectional perspective, it is hazardous to assume that the gender difference among whites or the racial difference among males has any direct bearing on the evaluation of the black female rate.

To move beyond merely descriptive quantitative analyses of intersectionality, a number of studies have used statistical modeling with the goal of detecting differences emerging from membership in multiple social categories. These studies have typically taken one of three approaches: using dummy variables, creating subsamples, and using interaction terms. We discuss each of these approaches in turn.

The first quantitative approach to operationalizing intersectionality involves the creation of dummy variables based on categorical variables. An example of this is the work of Collins et al. (2017), who use four dummy variables (white men, white women, nonwhite men, nonwhite women) with an ordered logit to examine whether perceptions of disparate treatment among legal professionals varied depending on race and gender. Similarly, Brown (2018) operationalizes racial/ethnic/nativity groups based on six dummy variables (non-Hispanic white, native born; non-Hispanic white, foreign born; non-Hispanic black, native-born; non-Hispanic black, foreign born; Mexican American, native-born; Mexican American, foreign born). The author then employs random coefficient growth curve models to examine how these intersectional conditions affect morbidity trajectories over the life course of respondents.

The advantage of the dummy variable approach is that it stays true to intersectionality's notion that each combination of categories constitutes a qualitatively distinct state. It further allows for a relatively straightforward comparison of coefficients within the same equation model, and the interpretation of the coefficients is likewise uncomplicated as the dummies may be treated statistically as interval variables. On the other hand, the dummy variable approach is typically restricted to relatively few categories and easily becomes complicated when the underlying attributes are not nominal level but interval or ratio level variables such as income or age, rendering its application less feasible. Further, the dummy variable approach is typically appropriate only if the variances of the different categories are at least roughly equal, which is frequently unlikely to be the case (Holgersson, Nordström, and Öner 2014). A dummy variable approach is also not advisable when the models for the different groups are likely to be substantially dissimilar (Harnois 2013), as is frequently implied by the idea that intersectionality shapes the experience of advantage and disadvantage.

The second approach seen in the literature involves splitting the original sample into subgroups and conducting a separate analysis for each subgroup. An example of this approach is Vespa (2009), who creates subgroups based on race and sex categories (black men, black women, white men, white women) and then estimates fixed-effects regressions for each subgroup, predicting changes in gender ideology. Analytically, this approach interacts every predictor variable with race and sex categories and then employs significance tests to compare estimates across models (Clogg, Petkova, and Haritou 1995). In a comparable manner, Mandel and Semyonov (2016) create separate linear regression models for blacks and whites along with indicator variables for women and men to examine racial gaps in earnings. Likewise, using data from the 1979 National Longitudinal Survey of Youth, Penner and Saperstein (2013) create separate logistic regression models for women and men and then estimate coefficients for the effect of social status on perceptions of race, while Harnois (2005) uses Structural Equation Modeling to estimate the salience of feminism in black and white women's lives.

Estimating subgroup models based on intersectional categories such as race, gender, and class allows the researcher to estimate separate coefficients for each category, thus offering flexibility in situations where it is likely that the underlying model is quite different for these groups. This flexibility, however, also comes with its own costs. The subgroup approach becomes unwieldy when the number of intersecting categories goes beyond two, as for instance the number of cases in each group will be substantially reduced, making it more difficult to detect the effects of intersectionality. Further, a comparison of coefficients across groups may relate to differences in intercepts only or to differences in intercepts and some or all slopes, complicating interpretation. Finally, such an approach again becomes complicated when the underlying attributes are not nominal level.

The third approach to quantitatively assessing the effects of intersectionality relies on the use of statistical interaction, arguably the default approach in situations where the effects of one variable depend on the value of another variable. The interaction-based approach builds on the view of intersectionality "as an analytic interaction: a non-additive process, a transformative interactivity of effects" (Choo and Marx Ferree 2010). As these authors note, such analysis should be "interaction-seeking and context sensitive" (146): it should assume important interactions across contexts as the default position and aim to embrace complexity rather than taking parsimony as its starting point. In the typical interaction-based approach to intersectionality, the focus is on net effects. Here, the additive model serves as a baseline, while the multiplicative term accounts for the conditional effects of intersecting categories on an outcome of interest (Rouhani 2014). It approaches intersections as "locations like 'street corners' where race and gender meet and have multiplicative effects; any 'street' (a social process, such as sexism or racism) can be seen as 'crossing' any other without being transformed itself" (Choo and Marx Ferree 2010:133).

In line with these arguments, a significant number of previous studies have used multiplicative terms to examine intersectionality. For instance, Baker and Whitehead (2016) use interaction terms in a logistic regression analysis to assess the relationship between gender, education, and political conservatism. Logan (2018) uses interactions between race and sexual behavior in a hedonic regression to evaluate the connection between masculinity and racial sexual stereotypes. Similarly, Pedulla (2018) uses interaction effects for unemployment status and race in logistic regression models to test for difference in callbacks from potential employers, while Penner and Saperstein (2013) use fully interacted models to test whether the effects of their focal variables were different for men and women.

Although Dubrow (2010:98) concludes that "for quantitative analysts wanting to account for intersectionality theory with existing survey data, interaction terms are the best way to measure intersections," interaction terms also have their drawbacks. Interactions beyond two terms are notoriously difficult to interpret, multiplicative terms become increasingly unreliable (e.g., Busemeyer & Jones 1983), and often large sample sizes will be required to detect interactions (e.g., Jaccard, Wan, and Turrisi, 1990). Further, as we discuss below, the interaction approach is fundamentally at odds with the view of intersectionality as a difference in qualitative states.

What emerges from this overview is a picture of multiple approaches to advancing quantitative research on intersectionality, yet each approach being limited and more or less appropriate depending on a variety of contextual factors (Harnois 2013). In the following section we explore further the relationship between conventional quantitative methods and the intersectionality perspective. We focus specifically on the use of tests of statistical interaction as a technique for assessing the 'extra penalty' linked to specific multi-attribute memberships.

INTERSECTIONALITY VERSUS STATISTICAL INTERACTION

Viewed through the lens of conventional quantitative analysis, the 'extra penalty' claim described above is seen as an assertion that a combination of traits such as *black female* in fact carries with it a *triple* penalty—one for being black, another for being female, and a third for combining these two traits. According to conventional quantitative analysis, this argument can be tested using a statistical interaction model: is there a statistically significant penalty for being a black female over and above the separate penalties for being black and for being female? While this way of approaching the 'extra penalty' question goes against the logic and the spirit of the intersectionality perspective as being about qualitatively different states, it is important to closely examine the application of the conventional test for interaction because, as noted above, it has been viewed by some as the proper test of intersectionality (e.g., Dubrow 2010).

Table 2 illustrates the setup for the test for interaction. We chose a simple design with two independent variables in a logistic regression, the statistical model chosen by a number of previous quantitative studies of intersectionality (e.g., Penner and Saperstein 2013; Baker and Whitehead 2016; Logan 2018; Pedulla 2018). In our design, X_1 assesses the impact of being black compared to being white, and X_2 assesses the impact of being female compared to being male. The test for interaction involves an assessment of the significance of the multiplicative interaction term X_1X_2, which captures the combined effect of the two traits. Note again that this cross-tabular representation of the data, which treats race and gender as independent variables and separates their effects, violates the basic principles of the intersectionality perspective, which views each intersection of traits as a qualitatively distinct state.

[Table 2 about here.]

The baseline poverty rate is 10% (.10). This is the rate for white males—the intersection of the two reference categories. The table shows a 10-point penalty for being female (cell 1 rate – cell 3 rate = 0.10), and also a 10-point penalty for being black (cell 4 rate – cell 3 rate = 0.10). The rate for black females is not shown in this table because it is specified at different levels in the demonstration that follows. Perfect additivity in *raw rates* would yield, as shown previously, an expected black female poverty rate of 30% (.30). However, perfect additivity in log odds yields an expected poverty rate of 0.36 for black females: (1/9)*(9/4)*(9/4) = an odds of 0.5625, which translates to a poverty rate of 0.36. Thus, it is important to note that the change in metric from proportions to log odds—a shift that is usually portrayed as substantively neutral—raises the 'extra penalty' threshold for black females from 0.30 to 0.36.

Table 3 shows the different black female poverty rates that are used in the tests for interaction that follow. The rates for white males, white females, and black males are held constant in these tests. The lowest black female rate is 0.3, which, as noted previously, is the rate that reflects perfect additivity in raw rates (no 'third penalty' for black females), but less than perfect additivity in the log odds metric (the black female rate falls short of perfect additivity).

[Table 3 about here.]

Which hypothetical poverty rates for black females support the contention that they are being penalized beyond what would be expected, given separate consideration of their race and gender? From a purely descriptive viewpoint, any effect beyond perfect additivity would seem to support the 'extra penalty' argument. Accordingly, the expectation is that an extra penalty certainly must exist for rows 3 through 6, where black female poverty rates exceed perfect additivity and range from a poverty rate of 0.42 to a rate of 0.60. In row 3, for example, the poverty rate for black females (.42) is more than double the rate for black males (.20), which constitutes strong descriptive evidence in support of the 'extra penalty' argument.

While the descriptive evidence is convincing, it still falls short of conventional standards and practices. From the perspective of conventional quantitative analysis, the 'extra penalty' (i.e., the interaction effect) must be statistically significant; otherwise, the more parsimonious additive model (no extra penalty) is preferred. In other words, from the perspective of conventional statistical analysis, it can be argued that black females are saddled with a triple penalty only if the coefficient for the interaction term is significant. Table 4 reports the results of the six tests of interaction, using the simulated data described in tables 2 and 3. Each test is based on an N of 400, with 100 observations in each race-gender category.

[Table 4 about here.]

The tests for interaction do not support the 'extra penalty' argument. The surprising result is that none of the tests yields a significant interaction effect, using a generous alpha of 0.05, not even when the observed black female rate is set at 60% in poverty, and thus triple the black male rate. What explains this surprising result? As the observed black female poverty rate increases, so do the coefficients for X_1 (race) and X_2 (gender) in the additive models, making it possible for the additive model to absorb most of the black female rate simply by adjusting the additive coefficients upwards. The major take-away here is that even an extreme *apparent* 'extra penalty'—a black female poverty rate of 60%—does not yield a statistically significant interaction effect. The additive models (shown in the last column of table 4) are more parsimonious and their likelihood ratio chi squares are not statistically inferior to those of the interaction models.[3]

These results challenge the use of conventional tests of interaction to assess 'extra' penalties. As noted previously, from an intersectional perspective it is not appropriate to posit the existence of a generic 'race effect' or a generic 'gender effect' in research assessing the intersectionality of race and gender. Instead, the different combinations of race and gender should be seen as a single variable, a multichotomy with as many categories as there are relevant *combinations* of traits. Tests of statistical interaction favor a baseline model that ignores combinations and focuses instead on the separate, net effects of 'independent' variables.

We turn next to our proposed set-analytic alternative to conventional quantitative methods for assessing intersectionality. As we will show, truth table analysis, a core feature of Qualitative Comparative Analysis (QCA), directly implements several of the central methodological concerns of the intersectionality perspective, providing a novel way to detect and evaluate the presence of 'extra penalties' due to multiple category membership.

A SET-ANALYTIC APPROACH TO INTERSECTIONALITY

The intersectionality perspective has several characteristics that are especially relevant to our set-analytic alternative to conventional quantitative methods. First, it locates social groups within a multi-attribute property space. Second, it is fundamentally comparative in nature, focusing on the contrasting experiences of individuals at different locations within this space. Third, it suggests that

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[3] A probit analysis of this data set yields similar results, with the exception that the row 6 results (with the black female poverty rate set at 0.6) yield a significant interaction effect ($p = 0.026$).

being at the intersection of social identity categories such as race and gender can (and usually does) entail qualitative distinctions, as multiple axes of difference interact and influence each other. Fourth, the intersectionality perspective assumes that relations between attributes are complex and cannot be reduced to generic, single-attribute effects (e.g., Hancock 2007b; Hankivsky and Cormier 2011; Collins 2015).

These characteristics of intersectional thinking dovetail with key features of Qualitative Comparative Analysis (QCA) (Ragin 1987; 2000; 2008; Ragin and Fiss 2017). The set-analytic approach of QCA treats each combination of attributes separately as a truth table row, and each row is evaluated independently with respect to its degree of outcome consistency (i.e., the degree to which cases with the combination of traits in each truth table row display the outcome in question). In effect, truth table rows constitute the categories of a single multi-attribute variable (Ragin 2000:71-78). As a result, set-analytic methods closely match the assumptions of the intersectionality perspective, leading several researchers to call for the greater use of QCA to study intersectionality (e.g., Hancock, 2007b; Cicca, 2016; Gross, Gottburgsen, and Phoenix 2016). Below, we focus on the use of both binary and fuzzy sets to capture intersectional categories, further demonstrating how a set-analytic approach can overcome some of the limitations associated with the use of dummy variables and subgroup analysis.

DATA

To illustrate the set-analytic approach, we use data from the National Longitudinal Survey of Youth (NLSY79). The truth table outcome is avoiding poverty; the intersectional conditions are gender (male/female), race (white/black), and parental income (not-low/low).

Avoiding Poverty. Our measure of poverty is based on the ratio of the respondent's household income to the official poverty level for that household. The denominator is based on the number of adults, the number of children, state of residence, and so on. The cut-off value for membership in the set of households *avoiding poverty* is a ratio of 1.0 (household income is the same as the poverty level). Households with poverty ratio scores greater than 1.0 are coded as *avoiding poverty*, while scores of 1.0 or less are coded as *in-poverty*.

Parental Income. To assess parental income, we use membership in the set of *not-low-income parents*. We assess parental income by first computing the ratio of parental income to the household-adjusted poverty level for the parents' household. The numerator of this measure is based on the average of the reported 1978 and 1979 total net family income. The denominator is the household-adjusted poverty level for that household. The cut-off value for membership in the set with *not-low-income* is a ratio of 3.0 (parents' income was three times the poverty level). Households with poverty ratio scores greater than 3.0 are coded as *not-low-income*, while scores of 3.0 or less are coded as *low-income*.

Race and *gender* are conventional binary sets. The three intersectional conditions modelled in the truth table are *race* (white = 1; black = 0), *gender* (male = 1; female = 0), and membership in *not-low parental income* (not-low = 1; low = 0).

ANALYSIS AND RESULTS USING BINARY SETS

Our analysis begins by constructing the truth table defined by the three intersectional conditions, which is shown in table 5. The three conditions yield a truth table with eight rows ($2^3 = 8$). Cases are sorted into truth table rows based on their values on the three intersectional conditions. Rows are sorted according to their consistency of poverty avoidance—the proportion of cases in each row avoiding poverty. The consistency scores range from 0.958 for white males with not-low income parents to 0.592 for black females with low income parents. The consistency of poverty avoidance scores for rows 2 through 8 are less than the score for white•male•not-low-parental-income (row 1), thus confirming the advantage of the row 1 combination.

[Table 5 about here.]

It is important to apply substantive criteria to evaluate the gaps separating row 1's consistency score from the other seven. As discussed previously, one such substantive criterion is the 'four-fifths rule.' Applying this rule involves dividing the proportions avoiding poverty in rows 2 through 8 by the consistency score for white•male•not-low-parental-income (row 1), the most privileged combination of conditions. These calculations are reported in the last column of table 5. Only row 8 violates the four-fifths rule: the value for row 8 (black•female•low-parental-income) is 0.592/0.958 = 0.618. Thus, application of the four-fifths rule to these data yields one combination of conditions that bears an 'extra' penalty when it comes to avoiding poverty.

The truth table approach to the study of intersectionality offers important additional analytical opportunities. Specifically, it is possible to compare the "extra-penalty" row (black females with low parental income—the bottom row) with its three logically "adjacent" rows—rows that differ from the extra-penalty row by only a single attribute:

white•female•low-parental-income	(race differs)
black•male•low-parental-income	(gender differs)
black•female•not-low-parental-income	(parental income differs)

These comparisons are important because they are directly relevant to the intersectionality perspective's position that a single difference between cases may constitute a difference in kind.

To assess differences between the extra-penalty row and its three logically adjacent rows, we use a three-step rubric. The first step employs *descriptive criteria*, assessing whether the out-of-poverty rate for the extra-penalty row is less than that of each of its adjacent rows. If the rate for the extra-penalty row is greater than any one of its three adjacent rows, there is no need to proceed to the next step. The test for the existence of an extra penalty has failed.

The second step employs *substantive criteria*, assessing whether the gaps between the extra-penalty row and its logically adjacent rows are substantively significant. In order to make this assessment, it is necessary to engage relevant external criteria such as the four-fifths rule. External criteria define what constitutes a meaningful gap. Using the four-fifths rule, if the out-of-poverty rate for the extra-penalty row is greater than 80% of the out-of-poverty rate for one or more of the adjacent rows, then there is no need to proceed to the third step. The test for the existence of an extra penalty has failed. However, in our example the results are consistent with the hypothesized extra burden:

black•female•low-parental-income vs. black•female•not-low-parental-income: .592/.810 = .731
black•female•low-parental-income vs. black•male•low-parental-income: .592/.772 = .767
black•female•low-parental-income vs. white•female•low-parental-income: .592/.784 = .755

Finally, the third step employs *statistical criteria*. Because consistency scores are proportions, Z tests can be used to assess the statistical significance of the difference between pairs of consistency scores. Are the gaps between the extra-penalty row and its three adjacent rows statistically significant? The three tests all yield significant Z values, indicating that the consistency of poverty avoidance for black females with low-parental income is significantly less than that of its three adjacent configurations. A pattern of results consistent with the existence of an extra penalty has been established.

Note that the three-step rubric excludes statistically significant gaps that fail the second step, which addresses substantive significance. Very often, small differences between the extra-penalty row and one of its adjacent rows is statistically significant due to the impact of large sample size. The three-step rubric excludes such findings by making the finding of substantive significance a precondition for the assessment of statistical significance.

ANALYSIS AND RESULTS USING FUZZY SETS

One decisive benefit of the truth table approach to the analysis of intersectionality is its facility for incorporating conditions that vary by level or degree as fuzzy sets. Fuzzy-set membership scores range from 0 (full non-membership) to 1 (full membership), with a score of 0.5 the cross-over point between 'more in' versus 'more out' of the set in question. Converting ordinal, interval, and ratio scales to fuzzy sets lays the foundation for set-theoretic manipulation of these conditions, which makes them suitable for truth table analysis. For example, the condition low-income-parents, which was dichotomized for the binary set analysis presented above, can be calibrated as a fuzzy set and included as a truth table condition. (See table 6.) We calibrated both not-low-income-parents and our outcome measure, avoiding-poverty, as fuzzy sets. We describe our calibration procedures in appendix 1.

[Table 6 about here.]

The degree of membership of each case in each truth table row is determined by the minimum of its memberships in the sets that make up the row. For example, the membership of a black female with a 0.25 membership in *not-low parental income* has a membership of 0.25 in the row that combines black, female, and *not-low parental income*; this same case has a membership of 0.75 in the row that combines black, female, and *low parental income* (membership in *low parental income* = 1 – membership in *not-low parental income*). This case has a membership of 0 in the other six rows because black females have 0 membership in white and also 0 membership in male. Table 6 also reports the number of respondents in each row, with *not-low parental income* dichotomized at 0.5 (the cross-over point for fuzzy sets) to simplify the tabulation of frequencies.

Truth table rows are listed according to their consistency of poverty avoidance, which is a set-analytic, proportional measure that assesses the degree to which respondents with the combination of attributes in each row constitute a subset of respondents avoiding poverty (see

Ragin 2008, chapter 3). In other words, it is an assessment of the degree to which the respondents in each row share the outcome in question—avoiding poverty. The calculation of consistency is as follows:

$$\text{consistency of } (X \leq Y) = \text{sum}(\min(X_i,Y_i)) \,/\, \text{sum}(X_i)$$

where X_i is degree of membership in the intersectional conditions in a given truth table row; Y_i is degree of membership in the outcome. The numerator assesses the intersection of sets X and Y; the denominator allows expression of the intersection relative to the sum of the memberships in set X. The resulting consistency score indicates the proportion of set X that is contained within set Y. Consistency scores close to 1.0 indicate that the respondents in a given row consistently display the outcome, avoiding poverty; scores less than 0.75 indicate substantial inconsistency. In general, if there are many cases with high row membership scores coupled with low membership in the outcome (poverty avoidance), then consistency scores are diminished accordingly.

The consistency of poverty avoidance scores shown in the penultimate column of table 6 range from 0.847 for white•male•not-low-parental-income to 0.383 for black•female•low-parental-income. In general, the consistency scores using fuzzy sets are lower than those using binary sets, and the gap separating the most advantaged respondents (row 1) from the least advantaged respondents (residing in row 8) is much greater. Note, however, that the rank order of the consistency scores is the same for binary and fuzzy set analyses.

Application of the four-fifths rule reveals that both black males with low-income parents and black females with low-income parents display consistency scores that are less than four-fifths of the white•male•not-low-parental-income value. The value for row 7 (black•male•low-parental-income) is 0.566/0.847 = 0.668; the value for row 8 (black•female•low-parental-income) is 0.383/0.847 = 0.452. Thus, application of the four-fifths rule to these data yields two combinations of conditions that bear an 'extra' penalty when it comes to avoiding poverty: one combination of two disadvantages for poverty avoidance (black• low-parental-income) in row 7 and a combination of three disadvantages (black•female•low-parental-income) in row 8.

More decisive from the viewpoint of the intersectionality perspective are the results of the comparison of row 8's (black•female•low-parental-income) consistency of poverty avoidance with the scores of its three logically adjacent rows. These comparisons address one of the core principles of the intersectionality perspective, namely, that differing on a single attribute can constitute a difference in kind. The perspective's 'extra penalty' hypothesis gains support if row 8's consistency score is less than the consistency scores of its logically adjacent rows, which it is, thus satisfying the first step of the three-step rubric for assessing whether an extra penalty exists.

The second step centers on the application of *substantive criteria*, operationalized in this example using the four-fifths rule. The results reveal that the consistency score for row 8 is less than 80 percent of each of its three adjacent rows:

black•female•low-parental-income vs. black•female•not-low-parental-income: .383/.692 = .553
black•female•low-parental-income vs. black•male•low-parental-income: .383/.566 = .677
black•female•low-parental-income vs. white•female•low-parental-income: .383/.687 = .557

These findings offer clear evidence of an extra penalty for black females with low parental income. This conclusion is reinforced further by the third step, which focuses on *statistical criteria*; all three tests yield significant Z values.

Note that even though the consistency of poverty avoidance for black males with low-income parents (row 7) is less than 80% of the white•male•not-low-income score (row 1), it would appear to fail the more strenuous extra-penalty test when compared with its logically adjacent rows (rows 3, 4, and 8). In fact, the black•male•low-parental-income poverty avoidance score is much greater than the rate for black•female•low-parental-income in row 8, and thus this combination would appear to fails the first step, which employs basic *descriptive criteria*. However, it is important to remember the relevant theoretical expectations when applying this test; the adjacent row 8 differs from row 7 on a condition (female) that would make poverty avoidance *more* rather than less difficult, and therefore our theoretical expectations would predict row 7 to have a higher poverty avoidance score than row 8. Hence, for row 7 the relevant comparisons are with rows 3 and 4, for which it passes the test of descriptive criteria.

DISCUSSION AND CONCLUSION

The idea of intersectionality has been at the core of a growing body of research suggesting that multiple social categories powerfully shape social inequalities. While this approach has its origins in qualitative research, recent work has shifted towards tracing the effects of intersectionality across populations, raising the question: how should researchers approach the analysis of patterns of intersectional disadvantage, using quantitative data? Our argument has been that current quantitative approaches based on correlational analysis and especially interaction effects have helped us move forward but still fall short. Conventional approaches based on statistical interaction are sometimes incapable of finding evidence of an extra burden, even when the extra burden is not only palpable, but dramatic. Our findings demonstrate that a test for significance of statistical interaction—the common approach to determining the presence of extra penalties—failed to detect an extra burden in our synthetic data even when the poverty rate for black females was three times that for both black males and white females and six time that of white males. Taking the theoretical and methodological challenges of conventional interaction-based tests for intersectional inequality as a starting point, we propose an alternative, set-analytic approach to examining intersectionality quantitatively. Drawing on tools from Qualitative Comparative Analysis (Ragin 1987 2000 2008; Ragin & Fiss 2017), we outline how a set-analytic approach closely aligns with intersectionality's core assumption that different combinations of attributes present different 'kinds' of cases. In fact, it closely aligns with several other characteristics of intersectionality: its comparative nature, its approach of locating social groups within a multi-property attribute space, and its assumption that relations between attributes are complex and combinatorial.

Applying a set-analytic approach to data from the NLSY79, the results we obtain indicate that our approach allows for a fine-grained analysis of intersectional advantage and disadvantage. Using both binary sets and fuzzy sets, we found strong evidence of extra penalty for black females with low-income parents. Their poverty avoidance rates were consistently less than 80% of the rates exhibited by logically adjacent combinations of characteristics. While we find the 80% rule a useful benchmark, other external standards could be applied with potentially different conclusions. The important point is that the chosen standard should be connected to practical concerns. While the use of statistical tests is an important component of the approach we recommend, they can be applied most fruitfully when combined with an external criterion such as the four-fifths rule or with benchmarks specified by policymakers. Using absolute as opposed to relative standards gives social research a better grounding in practical concerns and greater relevance to public issues.

In the current study we have focused on one particular life outcome, namely poverty. However, the set-analytic approach we have proposed is flexible in its application and can be used to examine the intersectionality of essentially any social category, be it nominal or graded, and can be applied to a wide variety of outcomes such as earnings, educational attainment, employment, divorce, incarceration, morbidity, ideology, and so forth. Similarly, following Smooth (2014), our approach can be used to examine not only the experience of marginalization but also that of privilege. Following this view, the intersectionality of social categories is not restricted to disadvantages; social inequalities co-occur and reinforce across the spectrum of social strata. Such arguments resonate with prior scholarship that has examined how both advantages and disadvantages are frequently cumulative in nature (e.g., Merton 1968; Nolan and Whelan 1999;

DiPrete and Eirich 2006; Lin and Harris 2010), and the set-analytic perspective lends itself to understanding the combinatorial nature of advantages as well as disadvantages.

While the set-analytic perspective we have outlined aligns closely with the fundamental assumptions of intersectionality, it has its own limitations, like any research approach. Specifically, the traditional multivariate correlational analysis with its focus on net effects is built around the notion of controlling for the effect of other, non-focal variables. Adding such control variables to an analysis is relatively inexpensive as long as they are theoretically grounded and there is a sufficiently large population of cases relative to the variables used. In contrast, adding explanatory measures to the kind of configurational analysis described here is costlier, as every additional measure doubles the size of the truth table. There are several strategies for coping with this limitation. Ragin & Fiss (2017) create macro-conditions that combine related conditions into a single set. For example, they combine parental income and parental education to create the macro-condition *favorable family background*. Furthermore, it is possible to incorporate control variables into the truth table analysis by residualizing the outcome variable (e.g., the ratio of income to poverty level) on control variables prior to calibrating it as a fuzzy set. For example, income to poverty level could be residualized on respondent's education (a control variable, not an intersectional variable), and then the residuals could be calibrated as a fuzzy set and used as the outcome in a truth table analysis.

In a similar vein, while our examples here have been limited to three intersecting disadvantages, a researcher might wonder whether more intersecting disadvantages might render assessing differences between the extra-penalty row and other rows quite laborious. It is of course correct that each additional condition doubles the size of the truth table and thus increases the number of possible comparisons between a focal truth table row and the other truth table rows. Accordingly, with three conditions there are eight rows and thus seven potential comparisons, with four conditions there would be 16 rows and 15 potential comparisons, and so forth. Fortunately, applying the four-fifth rule to a larger number of rows is of course quite simple when using a spreadsheet even with eight conditions and thus 255 comparisons, allowing the researcher to see at what point rows begin to violate the four-fifth rule, if they do so.

However, the exponential increase in the number of comparisons applies only for comparisons across *all* rows. When using our rubric with three criteria for examining adjacent rows, the situation is greatly simplified by the fact that the comparison is between one focal truth table row and the rows that differ from that row by one and only one condition. In other words, with three conditions there will only be three adjacent rows that differ by one condition from the focal row, with four conditions there will be four such adjacent rows, and with eight there would be eight adjacent rows, thus keeping the situation quite manageable. At the same time, this thought experiment would only apply to situations where in fact five to eight different disadvantages intersect. While conceivable, it seems that such situations are going to be fairly rare, but even if they exist, the effort involved in using our three criteria—descriptive, substantive, and statistical—for comparing the focal row with its adjacent rows would appear to be quite acceptable.

A researcher might also ask if the application of the truth table algorithm with its focus on parsimony is still conceptually aligned with the idea that different combinations of conditions present qualitatively different states. In this regard, there are two issues to consider. First, in the current study we primarily focus on using the truth table itself as an analytical tool to examine intersectionality by comparing individual rows—without applying Ragin's truth table algorithm. Our argument is that much can be gained from such an analysis at the level of the truth table itself. Second, when the focus shifts from comparing individual rows to looking across all truth table rows by applying Ragin's truth table algorithm, then indeed parsimony becomes an important consideration. However, even when applying the truth table algorithm, QCA still does not disaggregate each case into its scores on certain variables but retains the integrity of cases as configurations—by keeping the analysis at the level of the full truth table row—as QCA examines similarities and differences across cases. As such, the approach we offer here remains consistent with the intersectionality perspective even when applying the truth table algorithm. The key difference between examining individual rows and applying the truth table algorithm across all rows concerns goals: the former focuses on pinpointing decisive differences between selected rows, while the latter focuses on describing patterns in the truth table as a whole.

To conclude, the quantitative analysis of intersectional advantages and disadvantages has gained in importance over the last decade. Yet, its ability to offer insights regarding the presence of advantage and disadvantage across diverse groups has been compromised by methodological predispositions of conventional approaches. Here, we have offered an alternative that sidesteps these biases and closely aligns with the original intent of intersectionality, providing researchers with a template for the analysis of how multiple category memberships shape social outcomes.

APPENDIX 1: CALIBRATING FUZZY SET MEMBERSHIP SCORES

This appendix describes the calibration of the two fuzzy sets that we use in our fuzzy-set-theoretic analysis of the conditions linked to avoiding poverty.

Avoiding Poverty. To construct the fuzzy set of individuals avoiding poverty, we first calibrate respondents' degree of membership in poverty. We base our measurement on the official poverty threshold adjusted for household size and composition. The official poverty threshold is an absolute threshold (National Research Council 1996), meaning it was fixed at one point in time and is updated solely for price changes.

Our measure of poverty is based on the ratio of household income to the poverty level for that household. Using the direct method for calibrating fuzzy sets (see Ragin 2008, chapter 5), the threshold for full membership in the set of households *in-poverty* (fuzzy membership score = 0.95) is a ratio of 1.0 (household income is the same as the poverty level); the cross-over point (fuzzy membership score = 0.5) is a ratio of 2.0 (household income is double the poverty level); and the threshold for full exclusion from the set of households *in-poverty* (fuzzy membership score = 0.05) is a ratio of 3.0 (household income is three times the poverty level for that household).

The fuzzy set of households in poverty is a symmetric set; that is, it is truncated at both ends and the crossover point is set exactly at the halfway mark between the thresholds for membership and non-membership. Thus, the set of respondents *avoiding-poverty* is based on a straightforward negation of the set of respondents *in-poverty*. With fuzzy sets, negation is accomplished simply by subtracting membership scores from 1.0 (see Ragin 2008, chapter 2). That is, (membership in *avoiding-poverty*) = 1 − (membership *in-poverty*). For example, a case that is mostly but not fully *in* the set of respondents *in-poverty*, with a score of 0.90, is mostly but not fully *out* of the set of respondents *avoiding-poverty*, with a score of 0.10.

The use of a ratio of three times the poverty level for full membership in the set of cases avoiding poverty is a conservative cutoff value, but also one that is anchored in substantive knowledge regarding what it means to be out of poverty. For example, in 1989, the weighted average poverty threshold for a family of two adults and two children was about $12,500 (Social Security Administration 1998, table 3.E). Three times this poverty level corresponds to $37,500 for a family of four, a value that lies just slightly above the median family income of $35,353 in 1990 (U.S. Census Bureau, Historical Income Tables—Families, table F-7).

Parental Income. To assess parental income, we use degree of membership in *not-low-income parents*. We assess parental income by first computing the ratio of parental income to the household-adjusted poverty level for the parents' household. The numerator of this measure is based on the average of the reported 1978 and 1979 total net family income. The denominator is the household-adjusted poverty level for that household. The fuzzy set of respondents with not-low-income parents is similar in its construction to the fuzzy set of respondents avoiding poverty, described previously. That is, we first calculate the ratio of parents' household income to the poverty level, using NLSY data on the official poverty threshold in 1979, adjusted for household size and composition. Using the direct method of calibration, the threshold for full membership in the set with not-low parental income (0.95) is a ratio of 5.5 (parents' income was five and a half times the poverty level). Respondents with ratios greater than 5.5 times receive fuzzy scores between 0.95 and 1.0. Conversely, the threshold for full exclusion (0.05) from the set with not-low parental income is a ratio of 2 (parents' household income was only double the poverty level). Respondents with ratios less than 2 received fuzzy scores between 0.05 and 0. The cross-over point (fuzzy membership = 0.50) is pegged at three times the household-adjusted poverty level.

REFERENCES

Amundson, Kalynn, and Anna Zajicek. 2018. "A Case Study of State-Level Policymakers' Discursive Co-Constructions of Welfare Drug Testing Policy and Gender, Race, and Class." *Sociological Inquiry* 88 (3), August: 383–409.

Baker, Joseph, and Andrew Whitehead. 2015. "Gendering (Non)Religion: Politics, Education, and Gender Gaps in Secularity in the United States." *Social Forces* 94 (4): 1623-1645.

Browne, Irene, and Joya Misra. 2003. "The Intersection of Gender and Race in the Labor Market." *Annual Review of Sociology* 29: 487-513.

Busemeyer, Jerome R., and Lawrence E. Jones. 1983. "Analysis of Multiplicative Combination Rules When the Causal Variables Are Measured with Error." *Psychological Bulletin*, 93 (3): 549-562.

Choo, Hae Yeon, and Myra Marx Ferree. 2010. "Practicing Intersectionality in Sociological Research: A Critical Analysis of Inclusions, Interactions, and Institutions in the Study of Inequalities." *Sociological Theory* 28 (2): 129-149.

Christensen, Ann-Dorte, and Sune Qvotrup Jensen. 2012. "Doing Intersectional Analysis: Methodological Implications for Qualitative Research." *NORA - Nordic Journal of Feminist and Gender Research* 20 (2): 109-125,

Cicca, Rossella. 2016. "Qualitative Comparative Analysis as a Tool for Concept Clarification, Typology Building, and Contextualized Comparisons in Gender and Feminist Research." *Politics & Gender* 12 (3) E8: 1-7.

Clogg, Clifford C., and Eva Petkova, Adamantios Haritou. 1995. "Statistical methods for comparing regression coefficients between models." *American Journal of Sociology* 100 (5):1261–93

Collins, Patricia Hill. 2000. *Black Feminist Thought: Knowledge, Consciousness, and the Politics of Empowerment*. New York, NY: Routledge

Collins, Patricia Hill. 2015. "Intersectionality's Definitional Dilemmas." *Annual Review of Sociology* 41: 1-20.

Collins, Patricia Hill, and Sirma Bilge. 2016. *Intersectionality.* Malden, MA: Polity Press.

Contreras, Randol. 2018. "From Nowhere: Space, Race, and time in How Young Minority Men Understand Encounters with Gangs." *Qualitative Sociology*, 41: 263-280.

Crenshaw, Kimberlé. 1989. "Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory and Antiracist Politics." *University of Chicago Legal Forum* 1989: 139-167.

Crenshaw, Kimberlé. 1991. "Mapping the Margins: Intersectionality, Identity Politics, and Violence against Women of Color." *Stanford Law Review* 43 (6): 1241–79.

Cronin, Ann, and Andrew King. 2010. "Power, Inequality and Identification: Exploring diversity and Intersectionality amongst Older LGB Adults." *Sociology*, 44 (5): 876-892.

DeGraffenreid v. General Motors. 1976. 413 F. Supp. 142. *United States District Court, E. D. Missouri, E. D.*

DiPrete, Thomas A., and Gregory M. Eirich. 2006. "Cumulative Advantage as a Mechanism for Inequality: A Review of Theoretical and Empirical Developments." *Annual Review of Sociology* 32: 271-297.

Dubrow, Joshua Kjerulf. 2008. "How Can We Account for Intersectionality in Quantitative Analysis of Survey Data? Empirical Illustration for Central and Eastern Europe." *ASK Research & Methods* 17: 85-100.

Furstenberg, Frank F. 2007. *Destinies of the Disadvantaged: The Politics of Teenage Childbearing.* New York, NY: Russell Sage Foundation.

Gill, Rosalind. 2009. "Beyond the 'Sexualization of Culture' Thesis: An Intersectional Analysis of 'Sixpacks', 'Midriffs' and 'Hot Lesbians' in Advertising." *Sexualities* 12 (2): 137-160.

Gross, Christiane, and Anja Gottburgsen, Ann Phoenix. 2016. "Education Systems and Intersectionality." Pp. 51-72 in *Education Systems and Inequalities: International Comparisons*. Edited by A. Hadjar and C. Gross. Bristol: Policy Press.

Hancock, Ange-Marie. 2007a. "Intersectionality as a Normative and Empirical Paradigm." *Politics & Gender* 3 (2): 248-254.

Hancock, Ange-Marie. 2007b. "When Multiplication Doesn't Equal Quick Addition: Examining Intersectionality as a Research Paradigm." *Perspectives on Politics* 5 (1): 63–79.

Hancock, Ange-Marie. 2013. "Empirical Intersectionality: A Tale of Two Approaches." *U.C. Irvine Law Review* 3: 259-296.

Hancock, Ange-Marie. 2016. *Intersectionality: An Intellectual History*. New York, NY: Oxford University Press.

Harnois, Catherine E. 2005. "Different Paths to Different Feminisms? Bridging Multiracial Feminist Theory and Quantitative Sociological Gender Research." *Gender & Society* 19 (6): 809-828.

Harnois, Catherine E. 2013. *Feminist Measures in Survey Research*. Thousand Oaks, CA: Sage.

Harvey, Adia M. 2005. "Becoming Entrepreneurs: Intersections of Race, Class, and Gender at the Black Beauty Salon." *Gender and Society* 16 (6): 789-808.

Hauenstein, Neil M. A., and Jaron T. Holmes, Emilee B. Tison. 2016. "Detecting Adverse Impact: The Four-Fifths Rule Versus Significance Testing." *Public Personnel Management* 42 (3): 403–420.

Holgersson, H.E.T., and L. Nordström, Ö. Öner. 2014. "Dummy variables vs. category-wise models." *Journal of Applied Statistics* 41 (2): 233-241.

Hunting, Gemma. 2014. *Intersectionality-informed Qualitative Research: A Primer*. Vancouver, BC: Institute for Intersectionality Research and Policy.

Jaccard, James, and Choi K. Wan, Robert Turrisi. 1990. "The Detection and Interpretation of Interaction Effects Between Continuous Variables in Multiple Regression." Multivariate Behavioral Research, 25 (4): 467-478.

Leicht, Kevin T. 2008. "Broken Down by Race and Gender? Sociological Explanations of New Sources of Earnings Inequality." *Annual Review of Sociology*, 34: 237-255.

Lin, Ann Chih, and David R. Harris, eds. 2008. *The Colors of Poverty: Why Racial and Ethnic Disparities Persist* (National Poverty Center Series on Poverty and Public Policy). New York, NY: Russel Sage Foundation.

Logan, Trevon D. 2010. "Personal Characteristics, Sexual Behaviors, and Male Sex Work: A Quantitative Approach." *American Sociological Review* 75 (5): 679-704.

Lui, Lake. 2016. "Gender, Rural-Urban Inequality, and Intermarriage in China." *Social Forces* 95 (2): 639-662.

McCall, Leslie. 2005. "The Complexity of Intersectionality." *Signs: Journal of Women in Culture and Society* 30 (2): 1771-1800.

McQueeney, Krista. 2009. "We are God's Children, Y'All:" Race, Gender, and Sexuality in Lesbian- and Gay-Affirming Congregations. *Social Problems*, 56 (1): 151-173.

Merton, Robert K. 1968. "The Matthew Effect in Science. The Reward and Communication Systems of Science Are Considered." *Science*, 159: 56-63.

Meyer, Doug. 2012. "An Intersectional Analysis of Lesbian, Gay, Bisexual, and Transgender (LGBT) People's Evaluations of Anti-Queer Violence." *Gender and Society*, 26 (6): 849-873.

Morris, Edward W. 2007. "'Ladies' or 'Loudies'? Perceptions and Experiences of Black Girls in Classrooms." *Youth & Society*, 38 (4): 490-515.

Nolan, Brian, and Christopher T. Whelan. 1999. *Loading the Dice? A Study of Cumulative Disadvantage*. Dublin: Oak Tree Press.

Pedulla, David S. 2018. "How Race and Unemployment Shape Labor Market Opportunities: Additive, Amplified, or Muted Effects?" *Social Forces*, 96 (4): 1477-1506.

Penner, Andrew M., and Aliya Saperstein. 2013. "Engendering Racial Perceptions: An Intersectional Analysis of How Social Status Shapes Race." *Gender & Society*, 2 7(3): 319-344.

Ragin, Charles C. 1987. *The Comparative Method: Moving beyond Qualitative and Quantitative Strategies*. Berkeley, CA: University of California Press.

Ragin, Charles C. 2000. *Fuzzy Set Social Science*. Chicago: University of Chicago Press.

Ragin, Charles C. 2008. *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. Berkeley, CA: University of California Press.

Ragin, Charles C., and Peer C. Fiss. 2017. *Intersectional Inequality: Race, Class, Test Scores, and Poverty*. Chicago, IL: University of Chicago Press.

Rouhani, Setareh. 2014. *Intersectionality-informed Quantitative Research: A Primer*. Vancouver, BC: Institute for Intersectionality Research and Policy.

Smooth Wendy G. 2013. "Intersectionality from Theoretical Framework to Policy Intervention." Pp. 11-41 in *Situating Intersectionality: The Politics of Intersectionality*. Edited by A. R. Wilson. New York, NY: Palgrave Macmillan,

Valentine, Gill. 2007. "Theorizing and Researching Intersectionality: A Challenge for Feminist Geography". *Professional Geographer* 59 (1): 10-21

Walby, Sylvia, and Jo Armstrong, Sofia Strid. 2012. "Intersectionality: Multiple Inequalities in Social Theory." *Sociology* 46 (2): 224-240.

Yuval-Davis, Nira. 1997. *Gender and Nation*. London: Sage Publications.

Table 1. Hypothetical Poverty Rates by Race•Gender

Race•gender category	Poverty rate	N
Black females	.30	100
Black males	.20	100
White females	.20	100
White males	.10	100

Table 2. Hypothetical Rates of Poverty Cross-tabulated by Race and Gender

	$X_1 = 0$ (White)	$X_1 = 1$ (Black)
$X_2 = 1$ (Female)	Cell 1 N = 100 poverty rate = 0.20	Cell 2 N = 100 poverty rate = see table 3
$X_2 = 0$ (Male)	Cell 3 N = 100 poverty rate = 0.10	Cell 4 N = 100 poverty rate = 0.20

Table 3. Varying the Hypothetical Poverty Rate for Black Females

Row	White males N =100	White females N = 100	Black males N = 100	Black females N = 100
1	.10	.20	.20	.30
2	.10	.20	.20	.36
3	.10	.20	.20	.42
4	.10	.20	.20	.48
5	.10	.20	.20	.54
6	.10	.20	.20	.60

Table 4. Tests of Statistical Interaction

Row	Black female poverty rate	Black female poverty odds	X_1X_2 coef. (odds ratio)	Significance of interaction	Additive equation: constant, odds ratios for race and gender
1	.30	.4286	.7619	.610	$.1232+1.91 \cdot X_1+1.91 \cdot X_2$
2	.36	.5625	1.0	1.0	$.1111+2.25 \cdot X_1+2.25 \cdot X_2$
3	.42	.8276	1.287	.631	$.1001+2.64 \cdot X_1+2.64 \cdot X_2$
4	.48	.9231	1.641	.346	$.0899+3.09 \cdot X_1+3.09 \cdot X_2$
5	.54	1.174	2.087	.162	$.0802+3.63 \cdot X_1+3.63 \cdot X_2$
6	.60	1.5	2.667	.063	$.0711+4.29 \cdot X_1+4.29 \cdot X_2$

N = 400

Table 5. Assessing the Impact of Intersections of Race, Gender, and Class Background on Poverty Avoidance Using Binary Sets

Row	Race: White = 1 Black = 0	Gender: Male = 1 Female = 0	Parental income: Not low = 1 Low = 0	Frequency	Proportion avoiding poverty	Four-fifths rule applied
1	1	1	1	1180	0.958	--
2	1	0	1	1153	0.922	0.962
3	0	1	1	315	0.873	0.911
4	1	1	0	183	0.847	0.884
5	0	0	1	300	0.810	0.846
6	1	0	0	162	0.784	0.818
7	0	1	0	417	0.772	0.806
8	0	0	0	475	0.592	0.618

Table 6. Assessing the Impact of Intersections of Race, Gender, and Parental Income on Poverty Avoidance Using Fuzzy Sets and Subset Consistency

Row	Race: White = 1 Black = 0	Gender: Male = 1 Female = 0	Membership in not-low-parental-income or low-parental-income	Frequency	Consistency of poverty avoidance	Four-fifths rule applied
1	1	1	not low parental income	1180	0.847	--
2	1	0	not low parental income	1153	0.807	0.952
3	0	1	not low parental income	315	0.741	0.875
4	1	1	low parental income	183	0.700	0.827
5	0	0	not low parental income	300	0.692	0.817
6	1	0	low parental income	162	0.687	0.811
7	0	1	low parental income	417	0.566	0.668
8	0	0	low parental income	475	0.383	0.452