Intersectionality and quantitative methods: Assessing regression from a feminist perspective

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Abstract

This article examines the use of quantitative methods to advance feminist-inspired understandings of intersectionality. We acknowledge a range of conflicting opinions about the suitability of current quantitative techniques. To contribute to this debate, we assess the conceptualizations of intersectionality embedded in the most common approach to quantitative analysis, multiple regression. We identify three features of intersectional analysis highlighted in the feminist literature: 1) attention to context; 2) a heuristic approach to identifying relevant dimensions of inequality; 3) and addressing the complex, multidimensional structuring of inequality. Using these criteria, we evaluate: 1) multiple regression including context as a higher-order interaction; 2) multiple regressions run within different contexts and compared; and 3) multilevel regression including context as a higher-order level of analysis. We demonstrate with research illustrations that the models do a progressively better job at satisfying the criteria. We conclude that the third model offers a conceptualization of intersectionality that is the most consistent with the feminist literature.

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Introduction

In this paper we aim to contribute to the identification of quantitative methods suited to a feminist understanding of intersectionality. Scott (2010) identifies the value of quantitative methods for feminist-inspired research interests, and invites further consideration of appropriate quantitative techniques. Taking up this challenge, we focus on multiple regression analysis, as it is a commonly used quantitative technique in both academic and policy analysis. It has also been widely identified as an appropriate quantitative approach to intersectionality (Dubrow, 2008; Harnois, 2013; McCall, 2001; Spierings, 2012; Veenstra, 2011).[1] We undertake an assessment of the possible contribution of multiple regression to analyses of intersectionality, and we do so with specific criteria derived from the feminist literature. Our objective is to determine how well particular multiple regression approaches capture the conceptual underpinnings of feminist understandings of intersectionality

To some extent a concern with conceptual adequacy is addressed by practices of operationalization. As Fonow and Cook (2005) observe, a feature of feminist approaches to quantitative analysis has been to pay particular attention to operationalization in order to ensure a meaningful inclusion of a diversity of women's experiences. Questions about operationalization raise issues of conceptual adequacy by focusing on possibilities delimited by the construction of data. We approach conceptual adequacy from a different angle - one that is

[1] Our focus on multiple linear regression is not meant as a judgement on the relative value of other quantitative methods for analyzing intersectionality. For alternative possibilities, see Sigle-Rushton's (2014) discussion of non-parametric techniques (in particular, classification and regression trees, or CART) and Manderscheid's (2014) presentation of multiple correspondence analysis. We hope these alternatives will be subjected to the sort of interrogation we subject multiple regression to in this paper in order to add to the assessment of the adequacy of conceptualizations of intersectionality mobilized in specific quantitative techniques.

directed at the methods themselves. As Bowleg (2008) rightly notes, quantification approaches to intersectionality involve not only issues of measurement but also of interpretation. To elaborate on this point, different quantitative techniques offer different capacities for interpretation, and this is due in large part to how social processes are captured (or not) by the component parts and logic of the technique. To be clear about our intention in this paper, we want to turn attention to how the characteristics of quantitative techniques actively shape the interpretation, and position the operation, of the theoretical concepts under investigation. In other words, when applied to social science data, the mathematical structures of quantification techniques are not theoretically neutral. Specifically in our case, we want to examine the conceptualizations of intersectionality embedded in the mathematical structures of different forms of multiple regression. In so doing, we hope to identify which form of multiple regression is most closely aligned with the conceptualization of intersectionality in the feminist literature.

In the methodological and substantive literature addressing the use of quantitative techniques for the analysis of intersectionality, a range of opinions are expressed about whether anything suitable currently exists. This range, we suggest, coincides with variations in conceptualizations of intersectionality. More minimalist positions are generally optimistic about the viability of current approaches (see for example, Dubrow, 2008; Spierings, 2012). In contrast, those with more fulsome conceptualizations identify substantial limitations with available techniques (Dhamoon, 2011; Hancock, 2007; McCall, 2001; Sigle-Rushton, 2014). Even stronger positions consider the positivist assumptions of most quantitative research fundamentally incompatible with the central tenets of intersectionality (Bowleg, 2008).

Despite reservations, many are open to discovering techniques of quantitative analysis compatible with feminist approaches, and a major motivation to do so is the wish to promote feminist social justice claims in the development of policy and programs (Fonow and Cook, 2005; Harnois, 2013). As Hughes and Cohen indicate (2010:190) "quantification remains the 'gold standard' for much social science and policy-oriented research".

Thus, bringing a feminist understanding of intersectionality into research practices and evidence-based policy is important (Hankivsky and Cormier, 2011; Neysmith et. al., 2005; Winker and Degele, 2011) and requires addressing the capacity of quantitative methods to produce results that are experientially and theoretically meaningful.

To assess the conceptualization of intersectionality embedded in different forms of multiple regression, we begin by presenting the three criteria we have identified as central to a feminist understanding of intersectionality. We then move on to using these criteria to assess three different regression models. For each model, we provide an account of how well the three criteria are addressed, and present a research example to illustrate how the interpretation of intersectionality is shaped by the particular properties of the model. By engaging in this exercise we hope to help researchers recognise the conceptual choices being made when selecting particular analytical techniques, and to contribute to the identification of forms of regression analysis more fully compatible with feminist understandings of intersectional analysis.

What does the feminist literature identify as conceptually central to the analysis of intersectionality?

In asking this question, we are not suggesting that the conceptualization of intersectionality in the feminist literature is without debate. However, we would argue, as do others (Cho, Crenshaw and McCall, 2013; Choo and Ferree, 2010; Hughes and Cohen, 2010; Winker and Degele, 2011) that it is possible to identify some core conceptual commonalities. It is significant that these commonalities have been expressed as important in feminist discussions of both qualitative and quantitative approaches to intersectionality research. The three central characteristics we highlight here are the significance of context; a heuristic[2] orientation to the relevant dimensions of inequality; and embracing the complexity of the multidimensional structuring of inequality. They are closely related to each other but draw our attention to distinct theoretical, political and analytical issues.

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[2] We use the term heuristic to mean an open, exploratory orientation to analysis.

The importance of context is a ubiquitous comment in feminist discussions of intersectionality. The focus on context in intersectional analysis resonates with current trends in policy and program analysis which highlight the need to move beyond 'one size fits all' approaches, and toward more finely-tailored, contextually-specific, policies and programs. Similarly, the capacity of intersectional analysis to inform activism and strategies for social change depends on an analytical specificity that is contextually located. It is, therefore, crucial for the contexts of experience to be explicitly identified and brought into the analysis of intersectionality.

In highlighting the significance of a heuristic approach to analysis we refer specifically to arguments which advocate for a more exploratory orientation to determining appropriate dimensions of inequality. This means there should be no *a priori* assumptions about what factors of inequality are operating in any specific situation, and with what relation to each other. In the case of intersectional analyses of gender inequality, this argument is extended to gender itself meaning that its relevance for the configuration of inequality under analysis needs to be a question, not an assumption, of the research. Research experience and the literature will provide clues about what might be relevant in any particular investigation, but if we limit our analysis to what we already (think we) know, we close down possibilities for greater insight.

Attending to complexity is a prominent appeal in feminist discussions of intersectionality. The critique of additive conceptualizations has been further elaborated as encouragement to embrace the complexity of the multi-dimensional structuring of inequality. McCall's work (2001, 2005) was a turning point in identifying the strengths of quantitative analysis for such a purpose. This conceptual development directs our attention to how intersectionality is itself positioned in research investigations, and in particular, if it is positioned as an "add on" or as definitive of the overall structure of inequality. Further, Winker and Degele (2011) present a compelling case to extend the capacity of intersectional analysis to address complexity by bring in a multi-level approach capable of examining relations between structural and individual characteristics.

We use these three characteristics central to feminist conceptualizations of intersectionality - context, a heuristic orientation, embracing complexity - as criteria to compare and assess three regression models. While each of the three models marks an attempt to move beyond the limitations of standard regression procedures and additive conceptualizations of intersectionality, it is important to emphasize that the models differ from each other in whether or how the three characteristics are incorporated. We have organized our presentation of the three models in an order that indicates a greater capacity to incorporate context directly into the analysis. As we demonstate, this greater capacity regarding context, also offers more in terms of heuristic investigation and the analysis of complexity.

Model 1: Multiple regression including context as a higher-order interaction

One approach to analyzing intersectionality is to use standard multiple regression. This procedure isolates and adds together the impacts of independent variables (such as gender, occupation, education) on an outcome variable (for example, earnings). It then rectifies this artificial partitioning of experience through the use of interaction terms. Interaction terms are how intersectionality is conceptualized and operationalized in this approach.

Interaction terms are useful because they help identify *multiplicative* effects (Gujarati 2003) that may characterize inequalities beyond, or over and above, *additive* effects, where the linear influence of one explanatory variable (X_1) on an outcome (Y) changes as a result of variation in another variable (X_2). An example is when the impact of gender on income varies by minority status such that the wage penalty incurred by women is disproportionately borne by visible minority women. However, interaction terms, by themselves, contain important drawbacks with respect to our assessment criteria.

In the process of model building, the interaction term often constitutes a residual component. In such cases, interaction terms become relevant only after the 'main' effects are analyzed, rather than comprising a focus of the analysis as an intersectionality-driven approach would recommend. Moreover, for reasons related to interpretation and statistical power discussed further below, interaction terms, in and of themselves, may only provide a limited capacity to undertake a heuristic analysis exploring how intersecting factors could structure complex inequalities in a particular setting. That said, there are conceptual and technical ways of extending the logic and estimation of interaction effects that allow researchers to move closer to this kind of heuristic analysis. These extensions form the basis of Model 1. The fundamental difference between Model 1 and the conventional regression approach lies with a conceptual move towards treating interaction effects in a more complex fashion, and thus, more appropriately in terms of our assessment criteria.

To begin with, Model 1 attempts to situate interaction terms more centrally in the process of model building by acknowledging these terms are often *under-theorized* in contrast to additive main effects (Veenstra 2011:1). If the principal axes of social difference and inequality are fundamentally intertwined, as postulated by intersectionality, it follows that their intersection may take on different forms and levels of complexity that may not be captured by two-way interaction terms. Model 1 therefore emphasizes the need to consider higher-order interactions, such as those involving multiplicative relations between three variables (X_1, X_2 and X_3). The form of a three-way interaction is denoted by Equation 1:

Equation 1
$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4(X_1X_2) + b_5(X_1X_3) + b_6(X_2X_3) + b_7(X_1X_2X_3) + e$$

The significance test for b_7, or the regression coefficient for the three-way interaction, effectively determines whether such an interaction likely exists in the population under study. Coefficients for the two-way interactions (b_4, b_5, b_6) are interpreted in the same way, with the important difference that these coefficients are "conditionalized" on one another (Jaccard and Turrisi 2003:45-46). This means that for any two-way interaction, the other or absent predictor variable that appears in the three way interaction equals zero. For example, b_5 denotes the interaction effect for X_1 and X_3 when X_2 equals zero.

One way to theorize these higher-order interaction effects involves distinguishing a focal variable and, in the case of three-way interaction variables, first-order and second-order moderator variables. Before providing an example, we should ask a further question bearing on these distinctions as they apply to research on complex inequalities: what kinds of phenomena do interactions between inequality variables, such as gender, minority status and class, themselves interact with? As mentioned above, in order to move towards a more complex profile of inequality capable of informing localized policy and programme interventions, researchers need to consider how inequalities are configured across different contexts (such as neighbourhoods or labour markets). Given this orientation, it is useful to examine how two-way interactions interact with variables that offer such contextual insight.

Consider the following hypothetical regression results in Equation 2, showing the effects of gender, visible minority status and a continuous (contextual) variable denoting the number of high tech firms located within an individual's city or community (on a scale of one to 40). All possible pairwise interactions are included, as well as a three-way interaction.

Equation 2

$$\mathit{Ln(hourly\ earnings)} = -0.301 - 2.62\mathit{Female} - 1.52\mathit{Minority} + 0.37\mathit{HiTech}$$

$$t = (-0.280) \quad (-4.638)^* \quad (-2.058)^* \quad (5.826)^*$$

$$+\ 1.14(\mathit{Female}\text{X}\mathit{Minority}) - 0.33(\mathit{Female}\text{X}\mathit{HiTech}) - 1.10(\mathit{Minority}\text{X}\mathit{HiTech})$$

$$t = \quad (1.800) \quad (-0.805) \quad (-2.191)^*$$

$$-\ 0.53(\mathit{Female}\text{X}\mathit{Minority}\text{X}\mathit{HiTech})$$

$$t = \quad (\ 2.257)^*$$

$$R^2 = .227 \qquad n = 803$$

Suppose we conceptualize gender as our focal variable, and visible minority status as our first-order moderator variable. The coefficient for the two-way interaction between gender and visible minority status, 1.14, denotes the difference between the average gender gaps in log hourly earnings among those who identify and those who do not identify as a visible minority, when *HiTech* equals zero. Coding *HiTech* so that it centres around its mean (that is, so that the average is zero) reveals the difference between the mean differences for gender and visible minority status in the context of an average number of high tech firms (Jaccard and Turrisi 2003:56). The coefficient for *FemaleXHiTech* suggests that, relative to non-minority men, the hourly earnings of non-minority women decrease by exp(–.33) or 28% for each additional high tech firm. To compare the impact of each additional firm for the minority group, we subtract from this coefficient the value for the three-way interaction term between gender, minority and concentration of high tech firms, with the result that the hourly earnings of minority women decrease by exp(–.33 – .53) or 58% relative to minority men[3].

The three-way interaction, *FemaleXMinorityXHiTech*, is significant at the $p < .05$ level, providing support for the conclusion that a two-way interaction between gender and minority identification varies systematically according to the average number of high tech firms in the respondents' city. The coefficient for the three-way multiplicative term, –0.53, reflects the change in *Female*X*Minority* for a one unit increase in *HiTech*, meaning that for each additional high tech firm, the difference between the average gender differences for minority groups and non-minority groups grows by 41%, moving away from zero. As the high tech sector expands, it seems that the wage penalty paid by visible minority women becomes greater. Conversely, the earnings premium accorded to our comparison group (coded '0' for both gender and minority variables), namely white men, becomes larger with each additional high tech company.

Three-way interactions bring a more nuanced perspective of intersectionality to bear on regression, especially when a contextual variable (such as the character of a local labour market) is included as a component of the interaction. By including, and placing the onus of interpretation on, a higher-order interaction term, Model 1 moves closer to satisfying feminist criteria for intersectional analysis than standard regression. Nevertheless, Model 1 faces three important limitations. First, interaction effects are not estimated in isolation

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[3] Percentages are derived as the difference between one and the exponeniated logged odds.

from the main effects of the variables from which they derive. Rather, the significance of interaction effects is contingent on the size of main effects. As Dubrow (2008:n.p.) argues, "since main effects should be included in the model along with the interaction terms, the chance of finding empirical support for intersectionality theory is reduced." The issue is one of statistical power, because significance tests of interaction terms generally involve smaller sample sizes than tests of main effects and therefore have less statistical power for a given effect size. Bowleg argues (2008:319) that main effects "may swamp the effects of interactions between them," and that a "finding of significant main effects for all variables (i.e. race, gender, and sexual orientation) would signal a lower probability of finding a significant higher-order interaction." One way to address the problem of statistical power is to ensure a sufficiently large sample size. This limitation can also in part be addressed in a technical way by increasing conventional alpha levels to a higher cut-off, such as $p < .10$ instead of $p < .05$ (Veenstra 2011). These solutions may increase the possibility of significant three-way interaction effects, but they do not address how the model positions the interaction terms (and therefore, intersectionality) as an add-on to the main effects.

The second problem relates to difficulties in interpreting high-order interaction effects as well as the technical limitations encountered when moving beyond two-way interactions. As discussed by Brambor et. al. (2006) interpreting interaction terms is also challenging when both main and interaction effects are included in the model. These interpretive challenges and limitations can limit insights into intersectionality offered by interaction terms. A third issue relates to our understanding of the impact of contextual variables when they are conceived as independent variables in the regression model. While Model 1 allows the researcher to gauge how the impact of gender, minority status and other variables (and their intersections) vary according to differences in contextual variables, context is treated not as its own level of analysis but as an individual-level characteristic when present in the higher-order interaction terms. Thus, the exploration and assessment of its impact is limited.

In sum, the operation of intersectionality in Model 1 is restricted to the interaction terms of the regression equation. This affords some opportunity for a heuristic analysis in that various independent variables (including context-relevant independent variables) can be introduced and assessed. However, on both technical and interpretive grounds, Model 1 has a limited capacity to bring context and complexity into the analysis.

Model 2: Multiple regressions run within different contexts and compared

For a deeper appreciation of contextual variations of complex inequalities we must move beyond the analysis of main effects, control variables and interaction effects afforded by a single multiple regression model. Work by McCall (2001) and others, has done much to promote the value of analyzing complex inequalities within and between specific contexts, following the logic that determinants of complex inequalities are context-dependent. Indeed, attention to context plays a critical role in a heuristic examination of the particular dimensions of inequality operating in any given setting. It is also identified as a primary way of advancing quantitative analysis of complex inequalities (Bowleg 2008). Veenstra (2011:9), for example, argues that "[c]ross-contextual comparisons are essential in light of the fact that institutionalized race relations, gender relations, etc. are historically and contextually specific."

Model 2 moves further towards this goal by running separate regression models within different contexts and comparing relevant axes of inequality within and across contexts. This allows regression coefficients for additive and multiplicative effects to vary, which helps the researcher explore and determine, rather than assume *a priori,* what focal and contributing factors are operating in tandem to produce a unique configuration of inequality. Cross-contextual comparison can occur with varying degrees of formality. Informal and formal approaches will be discussed in turn.

To illustrate an informal cross-contextual comparison of inequality we refer to data from a study by Black and Veenstra (2011:87) which compares the intersecting impacts of place, race, gender and class on self-reported health in two large and diverse cities: Toronto and New York. Crucial to this approach, the survey data from the two cities used by the authors were similar in structure, collected around the same time (2003 and 2004), and covered the same variables of interest. Table 1 presents the odds of respondents reporting their

[Insert Table 1: An Example of Variation in Significant Gender Interactions between Two Contexts]

health as good or poor, a dichotomous measure that necessities the use of binary regression models. The odds ratios in bold are significant at a $p < .05$ level. The main additive effects for income, education and gender for each city are somewhat similar, although race/ethnicity plays a more significant role in NYC. However, comparing the interaction effects between the cities indicates there are some interesting differences. Specifically, gender and race interact in the case of Toronto, with South Asian women showing significantly higher odds (3.28) of reporting poor health than white women and men in general (in fact, South Asian men are significantly less likely than white men to report poor health). In contrast, no such interaction is observed for the case of NYC. Conversely, while an interaction between gender and education is observed in NYC, where the health penalty associated with not completing high school compared to completing college is significantly more severe for women (odds ratio = 2.133) than men (odds ratio = 1.461), this multiplicative impact is not observed in Toronto. In short, both the presence and the nature of interactive relationships appears to vary according to place.

The limitation of informal approaches to cross-contextual comparisons of complex inequality is that while they lend insight into possible sources of contextual variation, there is no way to confirm or statistically test whether this variation is responsible for observed differences between contexts. To formally test for a significant difference due to context, researchers require an integrated dataset so that 1) separate regression equations can be estimated for the categories of contextually-relevant variables, and 2) the average difference in the outcome variable across the different contexts can be partitioned into two parts, an explained component attributed to the impact of the explanatory variables, and an unexplained component attributed to the impact of context.

To illustrate this process, consider the results reported in a study by Gunderson and Krashinsky (2011) on gender differences in earnings associated with acquiring apprenticeship certification, as compared to other educational pathways such as non-apprenticeship trade programs and community college (these educational pathways will serve as our 'contextual' variable). Using 2006 Canadian census data, the authors first estimate a single baseline regression model, which shows some interesting effects regarding education. For both males and females, while controlling for other relevant variables, higher earnings are associated with higher levels of educational credentials, over and above the positive 4% increase (men) and 7% increase (women) that is associated with each additional year of education. However, the earnings return from an apprenticeship is starkly different for men and women. For instance, males who complete an apprentice program earn 9% more than males who do not finish high school, while females who complete an apprentice program earn 12% *less* than females who do not finish high school – all while controlling for other significant determinants of wage differences such as years of education, ethnicity and experience (Gunderson and Krashinsky 2011:11-12).

To further examine this substantial gender gap, Gunderson and Krashinsky estimate separate regression equations for each educational pathway, which allows all other wage determining characteristics to vary between apprentices and each comparison group that represents a viable educational alternative (i.e. high-school, non-apprenticeship certificate, and community college). They then decomposed the average earnings differential between these groups into the explained component (the part attributed to differences in average levels of wage-determining characteristics, or explanatory variables) and the unexplained component (the part attributed to differences in pay that apprentices and each comparison group receive for the *same* wage-determining characteristics)[4].

Table 2 shows the results of the decomposition. Column 1 shows the wage *premium* received by males for completing an apprenticeship relative to those with a high school education (24%), other trades (15%), and

[Insert Table 2: An Example of Decomposition Results: Returns to Apprenticeships, by Gender]

community college (2%), as well the wage *penalty* for female apprentices compared to the same groups, 7%, 1%, and 25% respectively. Columns 2 and 3 show, among males, the increasing importance of the explained component as the credentials for the comparison group increase, and simultaneous decrease of importance in the unexplained component. Among women we see the reverse effect. When compared to college graduates, the majority of the substantial pay penalty incurred by women (25%) is attributed to the unexplained component, or lower returns that female apprentices get for the same levels of wage determining characteristics. As the authors note, this relative disadvantage likely reflects the impact of occupational gender segregation on the availability of educational pathways, including apprenticeships (Gunderson and Krashinsky 2011:18).

Both informal and formal modes of comparing models across contexts speak to the role that context plays in structuring complex inequalities (we can picture, for example, cases where we could substitute for educational pathways regional labour markets, local governments or economic sectors). In this way, Model 2 offers a little more in terms of heuristic investigation due to the possibility of bringing more contextual information into the analysis. Technical operations such as the decomposition procedures in the formal cross-contextual comparison also offer greater opportunity to identify more complex variations in higher-order interaction relationships. However, like Model 1, Model 2 has the limitation that it is fundamentally based on data measured exclusively at the individual level of analysis. These models therefore do not incorporate into

[4] See Gunderson and Krashinsky (2011:13-15) for an account of their decomposition procedure.

the analysis variation that corresponds directly with the characteristics of contexts themselves. This is the primary advantage of Model 3.

Model 3: Multilevel regression analysis with context as a higher-order level of analysis

Conventional regression models, based on individual-level data, ignore the fact that people are ‘nested’ within various higher-order contexts that have their own characteristics, such as neighbourhoods, schools, workplaces, and localized labour markets. Of significance for intersectional analysis, this nesting can shape individual-level outcomes. In other words, inequality outcomes for individuals are likely to be a combination of their own characteristics and the characteristics of the social contexts in which they are embedded.

Model 3 is a multilevel regression analysis which has the feature of incorporating contextual information directly into a single regression model. A multilevel model uses a system of equations that identifies values of an outcome variable as a function of explanatory variables for individual characteristics (level 1) *and* explanatory variables for context level characteristics (level 2).[5] The conceptual underpinning of multilevel modeling is to explicitly account for the social contexts of inequality by animating context itself as a unit of analysis and source of variance.

Multilevel models animate context by estimating separate individual level regression equations for every category of the contextual (level 2) variable. For example, if level 2 comprised cities (W) and the outcome variable was wages (Y), then a separate earnings average would be calculated for each city included in the analysis. Furthermore, if X denoted education, a separate relationship between education and wages would be calculated for each city. Variation in cities shapes wage differences on an individual level, because both individual level earnings averages (intercepts) and education differentials (slopes) become regression outcomes

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[5] Expressed mathematically:
Level 1 (individual): $Y = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$. Level 2 (context): $\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_0$ and $\beta_{1j} = \gamma_{10} + \gamma_{11}W_j + u_{1j}$

themselves at this higher level of analysis. The strength of multilevel modeling rests on the fact that such slopes and intercepts are not only allowed to vary across a higher level population of groups or contexts, but that group characteristics can also be incorporated into a single integrated model[6].

Of critical importance to intersectionality, we can further explore how contextual characteristics reconfigure individual level relationships through the inclusion of a cross-level interaction, such as the multiplicative, multi-scalar impact of education and service growth on wages. This cross-level interaction may be significant if the impact of educational attainment on wage differences systematically differs between cities with high service growth and cities with low service growth. In sum, interactions in Model 3 not only become more than a residual term (a limitation of Model 1), and more than a product of data measured at the individual level (a limitation of Models 1 and 2), interactive relationships involving context itself become variables whose analysis contributes to our understanding of complex inequalities. Thus, Model 3 gives us the most elaborated analysis of complexity in that it has the capacity to explore intersectionality at the individual level as a dynamic structured by variations in the contexts of that experience. So, referring back to the research example in Model 2, instead of a comparison of intersectional inequality within and between two cities with city characteristics not included directly in the analysis, Model 3 allows us to explore how intersectional inequalities at the individual level vary (or not) by variations in characteristics of cities included explicitly in the analysis.

To illustrate the possibilities of Model 3, we offer an analysis of unpaid domestic housework, using microdata files for the 2006 Canadian census.[7] In what follows, we explore whether variation between neighbourhoods is related to hours of unpaid domestic labour (outcome variable) and, if so, whether this relates

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[6] The integrated model: $Y_{ij} = \underbrace{[\gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}W_j + \gamma_{11}W_jX_{ij}]}_{\textit{fixed}} + \underbrace{[u_{0j} + u_{1j}X_{ij} + r_{ij}]}_{\textit{random}}$

[7] See Bliese (2013) for a full technical description of the stages of multi-level modeling. Our aim in the description that follows is to convey the logic of the analytical process with a minimum of technical detail.

to gender and household income (level 1 explanatory variables) and the income profile of neighbourhoods (level 2 explanatory variable).[8]

Adopting a heuristic orientation to the significance of contextual factors, a key question is whether there is significant variation in hours of unpaid housework at the neighbourhood-level? If this is the case, there is justification for using neighbourhood as a contextual higher-order variable. In our analysis we established that variation in average hours of unpaid housework is significantly related to what neighbourhood you live in: higher income neighbourhoods have more unpaid hours of domestic work[9]. Therefore, bringing neighbourhood variation into the model as a level 2 contextual variable is justified and, by adding this to the model, our capacity for heuristic investigation and explanation expands.

With hours of unpaid housework in our model as both a variation between individuals (level 1) and between neighbourhoods (level 2), we can address the main purpose of the analysis - what explains differences in individual-level unpaid domestic work hours? We consider first the relation of income to domestic work hours at both level 1 and level 2. Specifically, we determine if falling below Statistics Canada's low income cut off (LICO) threshold will be significantly related to hours of unpaid housework[10]. These results are reported in Table 3.[11]

[Insert Table 3: Model Results for Relation of Income and Unpaid Housework Hours]

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[8] Unpaid housework is measured using five intervals, where 1=<5 hours, 2=5-14 hours, 3=15-29 hours, 4=30-59 hours, and 5=>59 hours. The census definition of unpaid household is "Number of hours that the person spent doing housework, maintaining the house or doing yard work without getting paid for doing so. For example, this includes time spent preparing meals, mowing the lawn, or cleaning the house, for oneself or for relatives, friends or neighbours" (Statistics Canada 2003:13). Neighbourhood is operationalized as a census tract. Census tracts are small, compact and relatively homogenous areas (between 2,500 and 8,000 persons) that correspond to easily recognizable physical features, and thus offer a reasonable proxy for neighbourhood.

[9] It may be the case that property owners and those with larger homes have more time and other resources to spend on unpaid housework.

[10] LICO is a common operationalization of household poverty in Canada and is used in Duncan (2010).

[11] Bliese (2013) refers to this as a "contextual model". The equation producing this table is $HWORK_{ij} = \gamma_{00} + \gamma_{10}(LICO_{ij}) + \gamma_{01}(N.LICO_j) + u_{0j} + r_{ij}$, where LICO refers to individual low income and $N.LICO_j$ refers to neighbourhood low income.

What the results in the table show is a significant, negative relationship between individual low income and hours of unpaid housework, and a significant, negative effect of neighbourhood low income *over and above* that of individual low income, suggesting multifaceted "contextual economic disadvantage" (Duncan 2010:573). In other words, the slope at the neighbourhood level (-1.095) differs substantially from the individual slope (-0.043), magnifying the negative impact of low income on average hours of housework. Lower individual income is associated with doing less hours of housework, and living in a low income neighbourhood further adds to the reduction of housework hours.

So far, we have demonstrated 1) the relevance of individual-level factors (low income) to within-neighbourhood differences of unpaid housework, and 2) the relevance of neighbourhood-level factors (low income) to between-neighbourhood housework differences. We now have a firm grounding to pose the question, following our heuristic orientation, are within-neighbourhood *relationships*, or slope differences, related to neighbourhood-level characteristics? We begin to address this more complex question by exploring variations between neighbourhoods in the relationship between average hours of housework and gender, and we expect a gendered effect whereby women perform significantly more housework on average than men.[12] We find, no surprise, that net of individual and neighbourhood low income, women perform significantly more unpaid housework hours. Of particular interest, however, is the examination of whether neighbourhood-level differences meaningfully contribute to the configuration of gender inequality in unpaid housework. Testing this possibility we find that this is indeed the case. Now we have a justification for including neighbourhood-level variance in the effect of gender as part of differences in unpaid hours of housework to be explained.

The above explorations indicate how the conceptual underpinnings of multilevel modeling support a heuristic approach to identifying relevant dimensions of inequality and sensitivity to context. We turn now to an

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12 Specifically, we allow a dichotomized gender variable (FM) to vary across neighbourhoods, estimating the following model: $HWORK_{ij} = \gamma_{00} + \gamma_{10}(LICO_{ij}) + \gamma_{20}(FM_{ij}) + \gamma_{01}(N.LICO_j) + u_{0j} + \boldsymbol{u_{2j}*FM_{ij}} + r_{ij.}$. The highlighted term tests whether or not neighbourhood variance impacts gender inequality in hours of housework.

aspect of multilevel modeling which operationalizes intersectionality as a complex, multi-scalar interaction involving context. In doing so, we are leaving behind the idea that intersectionality is contained in an interaction term, and moving closer to treating intersectionality as a feature of the overall structure of inequality.

A cross-level interaction, captured in the $\gamma_{21}(FM_{ij} * N.LICO_j)$ term in Equation 3 elegantly formalizes the proposition that unequal relations of gender and domestic work are relationships that themselves intersect in

Equation 3

$$HWORK_{ij} = \gamma_{00} + \gamma_{10}(LICO_{ij}) + \gamma_{20}(FM_{ij}) + \gamma_{01}(G.LICO_j) + \boldsymbol{\gamma_{21}(FM_{ij} * N.LICO_j)} + u_{0j} + u_{2j}*FM_{ij} + r_{ij}$$

particular ways with variations in contexts, in this case according to neighbourhood-level poverty. Specifically, the cross-level interaction examines whether neighbourhood-level poverty explains a significant amount of variation in the individual-level relationship between gender and unpaid housework.

Our unweighted estimates of average housework are reported in Table 4. They indicate the presence of

[Insert Table 4: Multilevel Regression Estimates for Unpaid Housework by Gender and Income]

a significant cross-level interaction (-0.178), although it is not immediately clear what form this interaction takes. Examining this cross-level interaction further,[13] we reach three conclusions. First, women perform more hours of unpaid housework on average than men each week in both poor (below-LICO) and more wealthy (above-LICO) neighbourhoods. Second, men and women in wealthier neighbourhoods perform more unpaid housework than men and women in low income neighbourhoods. Third, and finally, the gender difference in hours of unpaid housework work is itself dependent on the poverty profile of neighbourhoods. That is, gender inequality in hours of unpaid housework is significantly less in poorer neighbourhoods than in wealthier neighbourhoods.

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[13] To do this, we constructed a data plot following suggestions in Bliese (2013).

Results such as these suggest that intersections among individual-level data on central axes of inequality (gender, class, race) vary not only according to categories of other variables (Model 1), or within and across cross-contexual comparisons (Model 2), but also across variations in contexts identified as a higher-order level of analysis (Model 3). By offering the possibility to simultaneously investigate higher-order effects alongside conventional individual-level relationships, multilevel modeling is a powerful, context-sensitive approach to intersectionality. It supports a more heuristic exploration of what dimensions of inequality are operating in particular circumstances, and in what relationships with each other. By coming closest to meeting the three criteria we have identified for intersectional analysis, we believe it presents the most sophisticated regression approach to intersectionality.

Still, Model 3 is not without limitations. It has stringent dataset requirements: the researcher needs to be able to situate every respondent within theoretically significant contexts and in turn have access to information on all relevant contextual variables included in the analysis. Other challenges relate to weighting estimates, and, as with Model 2 and to a lesser extent Model 1, having a sufficient sample size. Generally speaking, however, applying multilevel modeling to complex survey data is a relatively recent development, and hopefully its greater alignment with feminist understandings of intersectionality might encourage further refinements in its application.

Conclusion

In this article we identify specific criteria for assessing regression analysis as a quantitative method appropriate for examining intersectionality as a complex configuration of inequality. What quantitative technique is most appropriate in any given case ultimately depends on the questions researchers aim to address and the data they have to work with. Causal regression models will not always be the best choice, but we focus on regression in this paper because it is a popular and influential choice among academic and policy analysts. In particular, regression continues to be a cornerstone of inequality research and policy analysis. Our analysis is based on the view that, when applied to social science data, mathematical models are not theoretically neutral. Our primary intention has been to assess the understanding of intersectionality embedded in different regression models in order to identify a regression approach most compatible with feminist understandings of intersectionality.

Drawing on feminist conceptualizations of intersectionality, we identify three criteria that appear in qualitative and quantitative discussions as core features: the significance of context, a heuristic orientation, and embracing the complexity of the multi-dimensional structuring of inequality. We then employ these criteria to assess three models of regression. We present arguments and evidence to support the conclusion that some regression approaches do better than others at capturing the conceptual underpinnings of feminist understandings of intersectionality.

While useful and widely practiced, standard multiple regression in which intersectionality is conceptualized as an interaction term, and extensions of this model (our Model 1) where context is included as a higher-order interaction, are fairly limited with respect to advancing complex understandings of intersectionality. In contrast, we found formally comparing multiple regressions runs within different contexts (Model 2), and multi-level regression (Model 3) that actually incorporates context as a higher-order level of analysis, offer greater capacity with respect to all three criteria. By incorporating context directly into the regression model as a higher-order level of analysis, multi-level regression offers the most sophisticated, and analytically elaborate, means of addressing context. As we argue and demonstrate, of the three models assessed it also offers the most in terms of heuristic possibilities, and the capacity to address complexity. Perhaps most importantly, where as Models 1 and 2 treat intersectionality as an add-on, marginal feature to the main effects in regression equations, multi-level modeling offers the opportunity to work with a conceptualization of intersectionality that positions it more centrally in the structuring of complex inequalities.

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Tables:

Table 1: An Example of Variation in Significant Gender Interactions between Two Contexts

		Odds Ratio	
		Toronto	**New York City**
Gender X race interactions			
Women	OR White (ref)	1.000	-
	OR Black	1.896	
	OR South Asian	**3.280**	
	OR Asian	1.010	
Men	OR White (ref)	1.000	
	OR Black	0.579	
	OR South Asian	**0.414**	
	OR Asian	1.007	
Gender X education interactions			
Women	OR less than high school	-	**2.133**
	OR high school graduate		1.181
	OR some college		1.162
	OR college graduate (ref)		1.000
Men	OR less than high school		**1.461**
	OR high school graduate		1.151
	OR some college		1.197
	OR college graduate (ref)		1.000

Source: Adapted from Jennifer Black and Gerry Veenstra, 2011, "A Cross-Cultural Quantitative Approach to Intersectionality and Health: Using Interactions between Gender, Race, Class, and Neighbourhood to Predict Self-Rated Health in Toronto and New York City," page 86 in *Health Inequities in Canada: Intersectional Frameworks and Practices*, edited by Olena Hankivsky, & Sarah De Leeuw, UBC Press.

Table 2: An Example of Decomposition Results: Returns to Apprenticeship, by Gender

Gender and Alternative Comparison Groups	Overall Gap ($\bar{Y}_a - \bar{Y}_n$)	"Explained" by Endowments ($\bar{X}_a - \bar{X}_n)\beta_n$	"Unexplained" or Coefficients ($\beta_n + \beta_a)\bar{X}_a$
Males			
Apprentice – High School Grads (n=377,044)	.2405 (100%)	.1100 (46%)	.1305 (54%)
Apprentice – Other Trades (n=185,005)	.1549 (100%)	.0982 (63%)	.0567 (37%)
Apprentice – College Grads (n=312,599)	.0232 (100%)	.0226 (97%)	.0006 (3%)
Females			
Apprentice – High School Grads (n=290,000)	-.0656 (100%)	-.0527 (80%)	-.0129 (20%)
Apprentice – Other Trades (n=89,151)	-.0112 (100%)	.0429 (383%)	-.0541 (-483%)
Apprentice – College Grads (n=283,752)	-.2470 (100%)	-.0424 (17%)	-.2046 (83%)

Data are for full-time workers only.
Source: Adapted from Morley Gunderson and Harry Krashinsky, 2011, *Table 2 – Decomposition Results, Full-Time Workers, by Gender and Comparison Groups* on page 23 in "Returns to Apprenticeship: Analysis Based on the 2006 Census."

Table 3: Model Results for Relation of Income and Unpaid Housework Hours

	Value	Std error	t-value	p-value
Intercept	2.159	0.003	639.740	<.0001
Low Income (Individual)	-0.043	0.002	-20.658	<.0001
Low Income (Neighbourhood)	-1.095	0.022	-49.892	<.0001

N=3484185, Census Tracts=5028
Canadian Census data , 2006

Table 4: Multilevel Regression Estimates for Unpaid Housework by Gender and Income

	Value	Std error	t-value	p-value
Intercept	1.732	0.002	886.249	<.0001
Low Income (Individual)	-0.067	0.002	-33.104	<.0001
Gender (Individual)	0.0560	0.002	320.942	<.0001
Low Income (Neighbourhood)	-0.990	0.022	-45.657	<.0001
Gender : Low Income (Individual x Neighbourhood)	-0.178	0.020	-8.952	<.0001

N=3484185, Census Tracts=5028
Canadian Census data, 2006