



Gender and intersectionality – a quantitative toolkit for analyzing complex inequalities

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Introduction – the importance of understanding gender, diversity and intersectionality for the analysis of inequality, and for the production of good policy and programmes

For some time now, researchers, analysts, policy makers and program developers have been working with the idea that **differences between men and women** in how they typically live their lives need to be considered when designing, and evaluating the impact of, policies and programs. Appropriate attention to **gender** – or the socially constructed differences in women’s and men’s lives - has been regarded as necessary for understanding gender inequality at societal, institutional and interpersonal levels, and for generating strategies for its eradication.

More recently, there is growing awareness of the importance of differences within gender categories – that is **differences between women and differences between men** – for a more nuanced understanding of gender inequality. In the literature on these more complex patterns of inequality, **differences within categories are identified as aspects of diversity that may have importance for identifying configurations of inequality**. So, for example, while women on the whole earn less than men, there are variations in women’s earnings such that non-visible minority women earn higher wages than visible minority women. Equally, men’s earnings vary by visible minority status – with non-visible minority men earning higher on average than visible minority men. These differences in earnings by visible minority status within gender categories can have an impact on the overall picture of gender inequality. Because the incomes of visible minority men are lower, it could be the case the gender differences in earnings in the visible minority population are less than gender differences in earnings in the non-visible minority population. That said, it is important to recognize that in the literature on complex inequalities, **diversity is also identified as both an aspect of individual identity and as a characteristic of aggregate groupings (such as institutions, cities or countries)**.

Because diversities of identity, experience and situation within each gender can have an impact on the profile of gender inequality, it is important for research, and for policy and program development, to look beyond aggregate gender differences, to see to how gender differences vary within particular situations or contexts. The extension of this logic is that there may be situations or contexts in which the main dimensions structuring inequality do not include gender.

Intersectionality is a way of thinking about this more complex profile of inequality. However, the complexities of inequality are such that analysts need to adopt specific orientations to research in order to be able to uncover the precise configuration of inequality in any specific context or population. Knowledge about how inequality is configured in a specific context (such as a city, a new immigrant group, a region, a province, an industry) is essential input for the development of policy and programmes designed to alleviate existing

problems or generate new provisions. An intersectional analysis encourages policy researchers to think about how social problems and policy outcomes are determined by a specific combination of an identifiable set of multiple dimensions. Focusing on the multiplicative effects of inequality dimensions can help to identify policy issues and social problems that are framed more precisely, and generate finely nuanced evidence from which to create socially relevant and inclusive policy solutions. Intersectional analyses can provide the detailed specifications of complex inequality configurations required to determine the equality-enhancing policy implementation strategies likely to be most effective for specific policy jurisdictions and locales.

The purpose of this tool kit is to provide guidance on the orientations to research required for an intersectional analysis of complex inequalities, and to help researchers and analysts appreciate the conceptual and technical advantages of specific quantitative approaches to intersectional analysis. While intersectional analysis can have other applications, the focus of this toolkit is on its application to the identification and understanding of inequality. It is this application of intersectional analysis that has been most prominent in the Canadian and international literature on contemporary gender experiences and structures. At HRSDC, intersectional analysis is an emerging practice. Currently, gender-based analysis (GBA) is the most common approach to integrating gender and diversity considerations in policy and program work, including research.

GBA, GBA+, and intersectional analysis – rationale, developments and challenges

Gender-based analysis (GBA) was developed as an analytical strategy to bring attention to gender into every aspect of the policy and programme process – from the earliest design stages through to implementation, evaluation, and communication. ***Gender mainstreaming*** – or the embedding of gender-based analysis in all procedures and responsibilities – is an active commitment in many international organizations as well as countries, and sub-national units, around the world. The Canadian federal government's commitment to the implementation of gender-based analysis in policy development, implementation and assessment is articulated in its presentation to the Fourth UN World Conference on Women in Beijing in 1995, *Setting the Stage for the Next Century: The Federal Plan for Gender Equality, 1995-2000*. HRDC was one of the leading federal departments to embrace GBA and was involved significantly in GBA training. Its contributions at this early stage included training manuals that became templates for other departments and for provincial offices across Canada, such as the well-regarded *Gender-based Analysis Guide: Steps to Incorporating Gender Considerations into Policy Development and Analysis* produced in 1997.

It is an important insight of GBA that its use can enhance the relevance and utility of government policies and programs for both genders. Systematically considering the impact of and on gendered experience can help to identify where stereotyped assumptions or insufficiently disaggregated analyses are inappropriately disadvantaging men versus women as well as vice versa. ***Because gender is a relational term*** – that is men’s social positioning can’t be understood in isolation from women’s social positioning – ***analytical approaches which consider the impact of gender, such as GBA, are as relevant for understanding men’s circumstances as they are for understanding women’s.***

In addition, the conceptualization of GBA has from the beginning included the awareness that gender categories are not homogeneous. In the *Federal Plan*, the Canadian government framed its commitment to GBA to include the recognition that gender-based analysis needed to be conducted with the importance of diversity acknowledged and integrated. For example, paragraph 23 states: “A gender-based approach ...acknowledges that some women may be disadvantaged even further because of their race, colour, sexual orientation, socio-economic position, region, ability level or age. A gender-based analysis respects and appreciates diversity.” ***While committed to bringing diversity into gender-based analysis, developing an appropriate research practice to do so proved to be challenging, particularly at more aggregate levels of analysis.*** The review of the five-year Federal Plan for Gender Equality by Status of Women (2001) highlighted the need for further progress in the development of analytic resources capable of reflecting diversity and its complex relations to gender. Recently, Status of Women Canada has been developing and promoting ***GBA+*** as an analytical strategy to address diversity and its significance for gender inequality. The ‘+’ signals advances in the conceptualization of GBA, and developments in analytical practices, to include more systematic attention to the significance of diversity in identifying profiles of gender inequality.

HRSDC has also been active on this front with its recent review and update of the department’s commitment to gender-based analysis. The manual on “Integrating Gender and Diversity into Public Policy” is a comprehensive and detailed presentation of strategies and practices to realize this commitment. Because of the importance of “differences between and within groups of men and women”, the manual also stresses the importance of “looking at the interconnections between various aspects of men and women’s identity and experiences” (2011:8). The point should be made that difference is not assumed by definition to mean inequality. The core idea is that differences within gender categories need to be examined to determine if any of the variation within gender is associated with more specific patterns of gender inequality.

Intersectional analysis pushes further in this direction by opening up the horizon of inequality analysis. It encourages a more heuristic exploration of what specific dimensions of inequality may be operating in particular circumstances. Instead of assuming *a priori* that certain dimensions are at work in structuring inequality in a specific setting, intersectional analysis begins with an exploration to determine which dimensions are operating, and

assesses if, where and how they are working in combination to produce a unique and complex configuration of inequality.

There is no specific research method for intersectional analysis. Qualitative, quantitative and mixed methods approaches are all used for producing the knowledge required to determine the role of gender in complex inequalities and the differential effects of policies and programs among and between different groups of men and women. Qualitative research has been the most predominant research approach. Developments in quantitative research have been hampered by a number of factors including issues of data availability and interpretive limitations of quantitative techniques. However, an interest in quantitative approaches to intersectional analysis is growing because it is thought that this approach to analysis offers insights into the structural configuration of inequality that may not be apparent from qualitative analysis alone.

A significant intervention in the analysis of complex inequalities, and in promoting the interest in quantitative intersectional analysis, is the work of McCall (2001). McCall distinguishes two forms of intersectional inequality analysis. One form is focused on the lived experience of individuals and groups positioned at specific intersections of inequality dimensions, and research on this form of intersectionality is typically qualitative. An example of this approach to intersectional analysis would be an investigation into the schooling experiences of young visible minority men to find out how the specifics of their intersecting experiences of gender, race and age are having an impact on their relation to education. Another example would be research into how women with higher degrees who emigrate to Canada under family class provisions fare in the labour market. In this case, the interest is in the specific intersections of gender, education, immigration status, and class of immigration. The complexity in these examples resides in how individuals embody and experience specific combinations of several dimensions of inequality.

This type of analysis is in contrast to one that attempts to look at a more aggregate, structural level of analysis, where, hypothetically, the full range of each dimension of inequality could be in play. So, for example, if education was operationalized as a variable indicating number of years of schooling after high school graduation – the analysis would be interested in examining all values of the education variable, not just a specific value. This would be the case with all variables in the analysis. A key focus of an intersectional analysis of this form is to identify which dimensions, and in what combination, are producing the more general pattern of observed inequality. An example of this approach would be analysis of inequality patterns in specific local labour markets to identify the impact and combination of gender, class, education, and race on observed wage inequalities. This is in fact the focus of McCall's own research. This form of intersectional analysis aims to uncover the structural configuration of complex inequalities and requires fairly sophisticated quantitative techniques capable of handling multiple relations between multiple inequality dimensions.

This quantitative toolkit will focus on the later type of intersectional analysis. However, we note at a number of points in the toolkit the importance of conducting qualitative research as a follow-up to quantitative analysis in order to fully understand the ways in which people live complex inequalities, and how policies and programmes can have an impact. An intersectional approach to complex inequality sees different expressions of inequality – the experiential and the structural - as inextricably connected. In other words, how individuals experience inequality in their daily lives is intimately tied to how inequality is configured as a characteristic of social structures (including institutions, laws, and government policies).

Basic features of an intersectional approach to inequality research and analysis

There are 6 basic features to how one approaches an intersectional analysis of complex inequalities, and we consider each of them below. We include here specific consideration of gender, as it has particular relevance for this toolkit, and there are issues to note with assumptions that are often made in quantitative analysis about the treatment of gender as a dimension of inequality.

i) consider gender as a dimension of inequality to be examined (not ignored or assumed)

Gender is a basic feature of the structure of inequality in Canadian society. Although progress toward gender equality has been made, it is important not to assume that gender inequality is no longer present or relevant. There are a number of ways that attention to gender can be ignored or marginalized in research – including lack of disaggregated data, assuming that research done on men's experience will apply to women (or vice versa), assuming that survey questions constructed with men's experience in mind will adequately cover women's experience (or vice versa), considering population means an adequate description of both women's and men's lives, and sampling in a way that skews the number of women and men and thereby limits the information on one or the other. Equally there needs to be caution in over-generalizing gender differences, in assuming difference necessarily means inequality, and in assuming rather than investigating how identified gender inequalities are to be explained.

An intersectional approach to the analysis of gender aims to include a gender as a variable and gender-related data fully in the analysis. It moves beyond binary thinking to consider gender as diverse, relational, constructed and amenable to change. That said, whether or not gender turns out to be a significant explanatory variable is a question to be investigated not assumed. While some people have difficulty accepting that we may need to regard the importance of gender as a question for analysis, rather than an assumption of it,

we must recognize that such a situation reflects any number of historical and specific conditions – including progress toward gender equality, or the profoundly negative realities of other forms of inequality and discrimination. This more open, heuristic approach to the analysis of gender is characteristic of intersectional analysis as a whole.

ii) avoid a priori assumptions about which dimensions of inequality will be relevant

This is a matter of adopting a heuristic attitude toward determining *what* dimensions of inequality are operating in any specific context. It is crucial to keep the identification of relevant inequality dimensions as open as possible in the first stages of intersectional analysis. Various intersectional researchers have introduced experiences of disability, religion, sexual orientation, citizenship status, language, nationality, migration experience, health status, household composition, employment history, locality, social networks among many others as relevant dimensions for an analysis of gender and intersectionality. This then means that it would be best to work with as comprehensive a data set as possible in terms of measured variables. A basic principle of intersectional analysis is that we cannot know in advance what dimensions of inequality are going to be relevant for any specific investigation or situation. Research experience and the literature will provide clues as to what might be relevant, but if we limit our analysis to what we already (think we) know, we close down possibilities for greater insight. This heuristic orientation to analysis begs two questions in terms of the practicalities of analysis: how do we know what variables need to be included; and how do we know when we have included enough? There is no easy formula to address these questions – for the answer is, you know you have the right variables and enough variables when your identification and interpretation of the complex inequality profile is convincing. What determines ‘convincing’? One strategy is to do follow-up qualitative research to see if the patterns identified in the quantitative analysis resonate with the lived experience of individuals living the identified intersections of inequality. Other strategies internal to a quantitative intersectional analysis are presented in the discussion of the 4 models to follow.

iii) avoid a priori assumptions about how inequality dimensions will be related to each other

This is a matter of adopting a heuristic attitude toward determining *how* dimensions of inequality are operating in any specific context. Analysts working with formulations of intersectionality generally reject any *a priori* notion of hierarchy among inequality dimensions. Working with a hierarchical notion of inequality dimensions means assuming that one dimension – for example, education – is the most important, and other dimensions

(such as gender, race, age, religion) are examined only as modifiers of the effects of education. The approach taken with intersectional analysis is to regard the relative positioning of dimensions of inequality as a variable feature of social relations and a question for the analysis to investigate. The importance of this point increases as analysts become increasingly interested in sub-national and more localized configurations of inequality. We cannot assume, for example, that the consequences for inequality of configurations of education, race, gender and age are going to be the same in Montreal as in Toronto or Ottawa.

iv) regard inequality dimensions as intersecting (not additive) aspects of inequality

Earlier forms of intersectional analysis tended toward an additive understanding of how multiple inequality dimensions relate to each other. An additive approach is where one would add to a gender analysis, considerations of race, class, disability, ethnicity, citizenship, age, visible minority status and so on. Dissatisfactions with this understanding soon emerged, particularly with the idea that these dimensions of inequality are somehow separate from each other – that if we are interested in the inequality experiences of Aboriginal young women we can somehow identify the meaning of each of these identities in isolation from the others. Current understandings emphasize the importance of understanding specific intersections of inequality dimensions as interconnected clusters of identity and socially structured experience. This means we have to pay particular attention to how intersectionality is conceptualized in quantitative analysis techniques, and aim for an operationalization of intersectionality that is not additive.

v) consider intersectionality as definitive of the overall structure of inequality

This consideration follows from the above point and relates to how intersectionality is operationalized within quantitative analysis particularly. Further information about this point is set out in later sections, for the moment it is sufficient to note that different approaches to quantitative analysis offer different ways to operationalize intersectionality. A limited version operationalizes intersectionality only as an interaction term in regression analysis. Intersectionality in this formulation occupies a minor place in the larger picture of inequality. A more fulsome version operationalizes intersectionality as an expression of the structural configuration of inequality. Intersectionality in this formulation is the larger picture of inequality.

vi) include in the analysis as much as possible about the context of experience

A highly influential aspect of an intersectional approach to the analysis of complex inequality is the idea that context matters. Intersectional analysis is an attempt to specify more precisely the processes and experiences of inequality. A consistent insight is that in order to do this well, context needs to be explicitly identified and if possible brought directly into the analysis. Therefore, it is important that as much information about the context of experience be included in the data set and the analysis.

This feature of 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 policies and programs. An interesting set of papers produced under the Status of Women’s *Integration of Diversity Initiative* around the turn of the century makes this point in relation to a number of policy objectives. For example, papers by Rankin and Vickers (2001), Bakan and Kobayashi (2000), and Kenny (2002) extend the logic of recognizing the significance of diversity within gender categories, to call for policy-delivery mechanisms that are as contextualized and situationally-specific as possible. More recent qualitative research by Neysmith et. al. (2005) presents this case very powerfully, as does the quantitative research of Dubrow 2008, Black and Veenstra 2001 and Veenstra 2011.

Key criteria for assessing the capacity and adequacy of regression models for intersectional analysis

We can summarize the basic features of an intersectional approach to the analysis of complex inequality by highlighting 3 features that provide key criteria for comparing different quantitative models. The three comparative criteria are:

- Compatible with a heuristic approach to intersecting patterns of gender and other inequality variables
- Interrogates the significance of context
- Moves beyond identifying intersectionality as a simple interaction term

Comparing 4 quantitative models for intersectional analysis of complex inequality

	Model 1	Model 2	Model 3	Model 4
	Standard multiple regression	Multiple regression including context as a 3-way interaction	Multiple regressions run within different contexts and compared	Multi-level regression analysis where context is a higher order variable
Analytical issues to consider				
Compatible with a heuristic approach to intersecting patterns of gender and other inequality variables	Limited	Yes, but under the constraints of a single equation	Yes	Yes
Interrogates the significance of context	No	Yes, but only as a higher order interaction effect	Yes, not directly in the model, but with the ability to test across models	Yes, directly in the model
Moves beyond identifying intersectionality simply as an interaction term	No	No	Yes	Yes

Model 1: Standard multiple regression

The first model and approach to analyzing intersectionality is the conventional approach defined by standard multiple regression. This approach will provide the 'baseline' model against which subsequent approaches will be compared in terms of their insight into context and heuristic capacity. The standard approach begins by estimating additive effects through the standard multiple regression equation:

Equation 1.1

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + e$$

For equation 1.1, suppose X_1 is gender, X_2 is visible minority status, X_3 is years of education, as a measure of social class, and the outcome or dependent variable, Y , is the natural log (ln) of hourly earnings. Here, variables such as gender and ethnicity are treated

as dummy variables, defined dichotomously as whether a respondent is male or female or belongs to a particular ethnocultural group, whereas educational attainment is a continuous predictor coded on a scale (e.g. with numerical values). In this approach gender, ethnicity and class are operationalized and examined as discrete phenomena (X_1 , X_2 , X_3) whose average effects (b_1 , b_2 , b_3) on hourly earnings (Y) are summed together as distinct causes or sources of variation. If gender is coded '1' for female and '0' for male, and ethnicity is coded '1' for identifying as a visible minority and '0' for not so identifying, then b_1 tells us the average income differential between females and males while b_2 tells us the average income differential between people who identify as belonging to a visible minority group and those who do not. Moreover, both of these regression coefficients report the impact each of gender and ethnicity (as simple binary measures) while controlling for the other as well as educational levels. Statistical control works to isolate the individual contributions of each variable.

This process gives the researcher a foundation for 1) determining the independent influence and relative significance of variables that are theoretically important to intersectional analyses, and 2) isolating these variables from other factors that may influence the outcome variable. However, this conceptualization of gender, ethnicity, class and other variables as isolated dimensions of a person's experience clearly runs against the grain of intersectionality research, for which the joint or co-constructed nature of these variables is not a starting point but a foundational premise. Thus, it is important to note that the standard model of multiple regression, on which subsequent techniques discussed below ultimately build, includes assumptions about the nature of social reality that sit uneasily with the basic tenets of intersectionality, especially as it is conceived by qualitative research. Nevertheless, as we will attempt to show, the researcher can address this tension by employing techniques that emphasize the intersectional and context-specific nature of complex inequalities.

To account for the compounding or *non-additive* impacts of key variables within the standard model, researchers typically include interaction variables to test for *multiplicative* effects (Gujarati 2003). Interaction terms are incorporated as additional variables after the so-called 'main effects' consisting of the variables that make up the interaction term are included and therefore controlled for:

Equation 1.2

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4(X_1X_2) + e$$

Interaction effects are often treated as the main vehicle for measuring intersectionality. They allow the researcher to determine how the impact of one explanatory variable (X_1) on a dependent variable (Y) changes as a result of variation in a third variable (X_2). In equation 1.2, for instance, if X_1 , X_2 and X_3 again represent gender, ethnicity and education, then b_4 , the regression coefficient for the interaction term X_1X_2 , denotes the multiplicative impact of gender and ethnicity on hourly wages, *over and above* that of each variable individually (b_1 , b_2), again while holding the impact of educational attainment constant. The significance test

or t test for b_4 , in turn, becomes a formal test of the null hypothesis of ‘no interaction in the population.’

For example, consider the following hypothetical regression results showing the average of log hourly earnings in relation to gender (coded ‘1’ for female), minority status (coded ‘1’ for belonging to a visible minority group), and educational attainment (measured as a continuous variable in years of education):

Example 1.1

$$\begin{aligned} \ln(\text{hourly earnings}) &= -0.213 - 1.70\text{Female} - 2.43\text{Minority} + 0.91\text{Edu} \\ t = & \quad \quad \quad (-0.201) \quad (-2.971)^* \quad (-3.951)^* \quad (10.051)^* \\ R^2 &= .271 \quad n = 728 \end{aligned}$$

where ‘*’ indicates a significance or p value of < 0.05 , or less than five percent. Taking the natural logarithm of hourly earnings is a conventional way of correcting the positive skew in its distribution, so each coefficient must be exponentiated for sake of interpretation. The coefficients are significant and have the signs we may expect. For example, the average of log hourly earnings for females, -1.7, suggests that females earn 82% less than males, because $\exp(-1.7) - 1 = -0.817$. Visible minorities, following the same procedure, earn 91% less than non-visible minorities, while education has a predictably strong, positive impact on earnings. Importantly, this model assumes that gender differences are constant across racial categories, and conversely that racial differences are constant across gender categories.

To test for more complex inequalities *within* categories of gender and racial categories we must estimate and interpret the appropriate multiplicative term:

Example 1.2

$$\begin{aligned} \ln(\text{hourly earnings}) &= -0.213 - 1.70\text{Female} - 2.43\text{Minority} + 1.75(\text{Female} \times \text{Minority}) + \\ & 0.91\text{Edu} \\ t = & \quad \quad \quad (-0.201) \quad (-2.971)^* \quad (-3.951)^* \quad (-1.651) \\ & (10.051)^* \\ R^2 &= .271 \quad n = 728 \end{aligned}$$

To interpret the interaction effect, it helps to first consider the coefficients for its component terms. In Example 1.1 the coefficient for *Female* reflects changes in earnings at each level of *Minority* and the coefficient for *Minority* reflects changes in earnings at each level of *Female*, depicting the general relationships between these variables. In contrast to this “main effects only” model (Jaccard and Turrisi 2003:24), in Example 1.2 the coefficients for *Female* and *Minority* reflect conditional relationships, namely the influence of gender and race when the other equals zero. In *Example 1.2* the regression coefficient for *Female* denotes the relative difference between non-minority women and non-minority men,

suggesting the former earn 82% less than the latter, while the coefficient for *Minority* suggests that minority men earn 91% less than non-minority men.

To find the relative difference between minority women and non-minority women, we add the coefficient for *Minority* with that of the interaction term *FemaleXMinority* ($-2.43 + 1.75$) and exponentiate the result, which shows that minority women earn 49% less than non-minority women. The interaction effect itself is insignificant at the 0.05 alpha level, lending support for the null hypothesis of no multiplicative effect. However, the actual significance value for *FemaleXMinority* is about .07. If we accept a 7% chance of incorrectly rejecting the null hypothesis, we can interpret the difference between minority and non-minority women as significant in the population, albeit not as substantial as the aforementioned differences between non-minority men and women and between minority and non-minority men. Finally, to test whether minority women have lower hourly earnings on average than non-minority men, we add the interaction coefficient with the coefficients corresponding to the additive variables for gender and visible minority status, or ($1.75 + -1.43 + 2.05 = -2.38$), and exponentiate. The result tells us that on average minority women earn 91% less than non-minority men, or the same differential observed of minority and non-minority men.

These insights afforded by the inclusion of the interaction effect show that gender and race do not necessarily intersect with hourly earnings in a straightforward, independent manner. Two implications can be drawn from this example regarding the analysis of complex inequalities. The first implication is that our assumption in an additive-only model of gender differences remaining constant across racial categories and racial differences remaining constant across gender categories is not always appropriate. Second, it suggests that women who belong to ethnocultural minority groups may face a compounded penalty or ‘multiple jeopardy’ as a result of simultaneously occupying multiple positions with low social status. That is, women who are racialized minorities may face an additional penalty in hourly wages over and above penalties associated with being either a woman or member of a visible minority group alone. By offering such insights, it is easy to see why interaction effects have become a prominent strategy in quantitative research and policy-based research.

Model 2: Multiple regression including context as a three-way interaction

However, interaction terms, by themselves, contain important drawbacks with respect to the core characteristics of intersectional analysis identified here, namely contextual insight and heuristic capacity. In the process of model building, the interaction term often constitutes a residual component or afterthought, as in the case when it is considered during the process of model checking rather than model construction. In such cases interaction terms only become relevant after the ‘main’ effects are analyzed and accounted for, rather than comprising a focus of analysis as an intersectionality-driven approach would recommend. Moreover, for reasons related to interpretation and statistical power discussed below, interaction terms, at least in and of themselves, may only provide a limited capacity to undertake a heuristic analysis of intersectionality that begins by exploring how intersecting factors could structure complex inequalities in a particular setting. Nevertheless,

there are conceptual and technical ways of extending the logic and estimation of interaction effects that allow researchers to move closer towards this kind of heuristic analysis. These extensions form the basis of Model 2. The fundamental difference between Model 1 and Model 2 lies with a conceptual move towards treating interaction effects in terms of the basic assumptions of intersectionality.

To begin with, Model 2 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 GBA+ and intersectionality, it follows that their intersection may take on different forms and levels of complexity that may not be adequately addressed by conventional, two-way interaction term analysis. That is, in some settings it may be as problematic to isolate two-way interactions from other variables as it is to isolate their main effects. Model 2 therefore emphasizes the need to consider higher-order interactions, such as those involving multiplicative relations between three variables. The form of a three-way interaction is denoted by equation 2.1:

Equation 2.1

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

The significance test for b_7 or the regression coefficient for the three-way interaction, as in the case of such a test for two-way interactions, effectively determines whether or not 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 as described above, 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 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 gender, ethnicity and class themselves interact with? As mentioned above, in order to move towards a more complex profile of inequality that can inform local policy interventions, researchers need to consider how inequalities are actually configured across different contexts, such as cities, provinces, economic sectors, labour markets, etc. Given this orientation, it is useful to examine how two-way interactions themselves interact with variables that offer such contextual insight. Consider the following hypothetical regression results, showing the effects of gender, minority status and a continuous variable related to labour market conditions denoting the number of high tech manufacturing establishments located within an individual’s city or community (on a scale of one to 40). Additionally, all possible pairwise interactions are included as well as a three-way interaction.

Example 2.1

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

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

$$+ 1.14(\text{FemaleXMinority}) - 0.33(\text{FemaleXHiTech}) - 1.10(\text{MinorityXHiTech})$$

$$t = (1.800) \quad \quad \quad (-0.805) \quad \quad \quad (-0.191)^*$$

$$- 0.53(\text{FemaleXMinorityXHiTech})$$

$$t = (-0.257)^*$$

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

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 can help contextualize this difference between two mean differences as that observed for an average number of high tech companies (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 company. 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, race and concentration of high tech sector companies, with the result showing that the hourly earnings of minority women decrease by $\exp(-.33 - .53)$ or 58% relative to minority men.

The three-way interaction, *FemaleXMinorityXHiTech*, is significant at the $p < .05$ level, providing support for the hypothesis that a two-way interaction between gender and race varies systematically according to the average number of high tech companies with which respondents are proximate. The coefficient for the three-way multiplicative term, -0.53 , reflects the change in *FemaleXMinority* for a one unit increase in *HiTech*, meaning that for each additional high tech company 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 may be the case that the penalty paid by women who also identify as a visible minority becomes greater and greater. Conversely, the premium accorded to our comparison group (coded '0' for both gender and ethnicity variables), namely white men, may become larger with each additional high tech company. To further explore these possibilities, in addition to this "difference in relative differences" we need to consider the other two-way interactions to see how high tech concentration impacts each particular subgroup. The coefficient for *HiTech* shows that each additional firm results in an $\exp(0.37)$ or 45% increase in hourly earnings for non-minority men. Subtracting the

coefficient for *MinorityXHiTech* from this value shows that among minority men each additional firm, by contrast, results on average in an $\exp(0.37 - 1.10)$ or -52% difference in hourly earnings. For non-minority women, each additional firm results in an $\exp(0.37 - 0.33)$ or $+4\%$ difference, while for minority women each additional firm results in an $\exp(0.37 - 0.33 - 1.1 - 0.53)$ or -80% difference. Looking at the impact of high tech concentration on each subgroup shows that race and gender do indeed interact with respect to the number of proximate companies, with racialized women paying the highest penalty.

While three-way interactions yield a more nuanced approach to gender inequalities and intersectionality, especially when a contextual variable is included as a component of the interaction, thus giving the researcher or policy analyst the capacity to establish a more complex profile of inequality, Model 2 faces three important limitations. First, interaction effects are not estimated in isolation from the main effects of the variables from which they derive. Rather, the significance of interaction effects are 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. Some argue 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, sex, and sexual orientation) would signal a lower probability of finding a significant higher-order interaction” (Bowleg 2008:319). 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 our conventional alpha levels to a higher cut-off, such as $p < .10$ instead of $p < .05$ (Veenstra 2011), as alluded to above in the examples used for Model 1 when we decided to interpret an interaction coefficient even though it was only significant at a $p < .07$ level.

The second problem relates to difficulties of interpretation surrounding interactions, especially for higher-order interaction effects. As we saw in the example above, the meaning of first and second-order interaction coefficients is contingent not only on how we conceptualize each variable, it also depends on controlling for each variable in the equation. Because main effects should generally be included in the model with interaction terms (Brambor et al. 2006), and because interaction terms are often at a disadvantage with regards to statistical power, these terms thus face both interpretive and technical challenges that may limit their insight into intersectionality and contextual variation of inequality. The final limitation relates to our understanding of the impact of contextual variables when they are conceived as independent variables in the regression model. While Model 2 allows the researcher to gauge how the impact of gender, ethnicity and other variables (and their intersections) varies according to differences in contextual variables, the coefficients of our focal independent variables and controls are fixed at average or particular values of contextual variables.

Model 3: Multiple regressions run within different contexts and compared

To gain a deeper appreciation of contextual variation in profiles of complex inequality we must move beyond the analysis of main effects, control variables and interaction effects in a single multiple regression model. Because the structure of inequality as an intersection of gender, ethnicity and social class varies according to the context (McCall 2001), in terms of labour market conditions, immigration profiles, population sizes, urbanization and many other *place*-based variables, it follows that social determinants of inequality should be allowed to reflect the contextual variation that occurs between different places. Indeed, attention to sociocultural, historical and economic context, which plays a critical role in a heuristic examination of what particular dimensions of inequality may or may not be operating in any given setting, is seen among intersectionality researchers as a primary way of advancing quantitative analysis of complex inequalities (Bowleg 2008). Gary Veenstra (2001:9), for example, argues that “cross-contextual comparisons,” such as Canada and the United States or different regions within these diverse countries, “are essential in light of the fact that institutionalized race relations, gender relations, etc. are historically and contextually specific.”

Model 3 moves towards this goal by emphasizing the need to run separate regression models in different contexts and compare relevant dimensions of inequality across model results. This allows regression coefficients for additive and multiplicative effects to vary, which helps the researcher explore and determine, rather than assume a priori ahead of time, 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. When informally comparing regression results for parallel models of inequality drawing on datasets collected in different settings, it is important to note that differences in survey design, sampling, question wording, time frame and other confounding factors can render cross-contextual comparisons difficult, if not entirely inappropriate. In such cases, differences between models may have little to do with what is actually going in the populations of interest. When conducting these kind of comparisons, therefore, the more similarities between the surveys, and the closer together in time they were conducted, the better, particularly given the changing nature of the ways in which people understand and respond to similar survey items.

For an illustrative example of an informal cross-contextual comparison of inequality consider the following table, produced by a recent study conducted by Black and Veenstra (2011:87). The study examines the intersecting impacts of place, race, gender and class on self-reported health between two large and diverse cities: Toronto and New York City.

An Example of Variation in Significant Gender Interactions between Two Contexts

			Odds Ratio	
			Toronto	New York City
<i>Gender X race interactions</i>				
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	
<i>Gender X education interactions</i>				
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: Extract from Jennifer Black and Gerry Veenstra, pg. 86, 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," in *Health Inequities in Canada: Intersectional Frameworks and Practices*, edited by Olena Hankivsky, & Sarah De Leeuw, UBC Press.)

The survey data used by the authors were similar in structure, collected around the same time (2003 and 2004), and covered the same variables of interest. The table reports the odds that certain respondents reported their health as being good or poor, a dichotomous measure that necessitates the use of binary regression models. The odds ratios in bold are those that are significant at a $p < .05$ level. While the main additive effects for race, income, education and gender for each city were somewhat similar, although race/ethnicity played a more significant role in NYC, some interesting points of divergence emerged between these contexts at the interactive level. Specifically, gender and race interacted 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 were significantly less likely than white men to report poor health). In contrast, no such interaction was observed for the case of NYC. Conversely, while an interaction between gender and education was observed in NYC, where the health penalty associated with not completing high school compared to completing college was significantly more severe for women (odds ratio = 2.133) than men (odds ratio = 1.461), this multiplicative impact was not observed in Toronto (Black and Veenstra, 2011:85). In short, both the presence and the nature of interactive relationships appeared to vary according to place.

The key limitation of informal approaches to cross-contextual comparisons of complex inequality is that while they lend insight into possible sources of place-based variation, there is no way to confirm or statistically test whether this variation is responsible for observed differences between groups. To formally test for this possibility, researchers require an integrated dataset on the basis of which 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 regression models can be decomposed into two parts, one attributed to the impact of the explanatory variables (the explained component), and the other attributed to differences between the models while keeping the regression coefficients constant (the unexplained or coefficient component). The unexplained/coefficient component denotes the impact of variation in the contextual variable as well as unobservable factors overlaying this variation.

Log Earnings Coefficients for Education by Gender, Full-time Workers, 2006 Census

Variable	Males			Females		
	Mean	Coef.	t-stat	Mean	Coef.	t-stat
	(1)	(2)	(3)	(4)	(5)	(6)
(Less than high school)						
High school grad	0.243	0.030	11.22	0.256	0.032	10.84
Trade certificate	0.088	0.050	15.50	0.066	-0.039	-9.95
Apprenticeship	0.061	0.092	21.83	0.018	-0.117	-19.48
Community college	0.191	0.114	27.20	0.249	0.089	20.41
Some university	0.043	0.172	34.31	0.057	0.203	39.69
University grad	0.146	0.291	49.20	0.174	0.259	40.42
Some post grad	0.022	0.294	36.46	0.029	0.270	33.65
Master degree	0.047	0.320	39.53	0.044	0.281	32.34
PhD	0.012	0.412	37.09	0.006	0.303	22.84
Medical degree	0.008	0.965	77.48	0.006	0.716	49.03
Education (years)	13.296	0.044	49.19	13.546	0.072	72.90

(Source: Extract from Morley Gunderson and Harry Krashinsky, 2011, "Returns to Apprenticeship: Analysis Based on the 2006 Census.")

To illustrate this process, consider Table 2, taken from a study conducted by Gunderson and Krashinsky (2011) on differences in earnings between men and women 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 Census data, the first Canadian Census to include data on apprenticeship certification, the authors first estimated a single baseline regression model. Table 2 shows their results for the educational variables (while controlling for other relevant variables, not shown). The coefficients in column 2 and column 5 show that in general, for both males and females, 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 return in earnings 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.

An Example of Decomposition Results: Apprentices, by Gender, Full-time Workers

Gender and Alternative Comparison Groups	Overall Gap (Ya–Yn) (1)	“Explained” by Endowments dotations (Xa –Xn)βn (2)	“Unexplained” or Coefficients (βa – βn)Xa (3)	Sample Size (4)
All Apprentices				
Males				
Apprentice – High School Grads	0.2405 (100%)	0.1100 (46%)	0.1305 (54%)	377,044
Apprentice – Other Trades	0.1549 (100%)	0.0982 (63%)	0.0567 (37%)	185,005
Apprentice – College Grads	0.0232 (100%)	0.0226 (97%)	0.0006 (3%)	312,599
Females				
Apprentice – High School Grads	-0.0656 (100%)	-0.0527 (80%)	-0.0129 (20%)	290,000
Apprentice – Other Trades	-0.0112 (100%)	0.0429 (383%)	-0.0541 (-483%)	89,151
Apprentice – College Grads	-0.2470 (100%)	-0.0424 (17%)	-0.2046 (83%)	283,752

(Source : Extract from Morley Gunderson and Harry Krashinsky, 2011, “Returns to Apprenticeship: Analysis Based on the 2006 Census.”)

To further examine this substantial gender gap, Gunderson and Krashinsky estimated 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 alternative for apprentices (i.e. high-school, non-apprenticeship certificate, and community college). They then decomposed the average earnings

differential between these groups (Gunderson and Krashinsky 2011:13-15) into the explained component (the part attributed to differences in average levels of wage-determining characteristics, or explanatory variables) and the unexplained or coefficient component (the part attributed to differences in pay that apprentices and each comparison group receive for the *same* wage-determining characteristics), using an equation called the Blinder-Oaxaca decomposition:

Equation 3.1

$$(Y_a - Y_n) = (X_a - X_n)\beta_n + (\beta_n - \beta_a)X_a$$

where Y is the mean log of earnings

X is the mean values of a vector of various explanatory variables

β is a vector of regression coefficients for said explanatory variables

a denotes apprentices

n denotes non-apprentice comparison groups

Table 3 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 trade (15%), and 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 of 25% is attributed the unexplained component, or lower returns that female apprentices get for the same levels of wage determining characteristics. Apprenticeship trades appear to be significantly disadvantageous for women, which as the authors note in their conclusion likely reflects the concentration of female apprenticeships in low-wage service jobs (Gunderson and Krashinsky 2011:18), and further work is necessary to understand how different occupational and city contexts mediate the impact of these educational pathways on earnings (2011 pg. 5-6).

While running separate regressions within categories of variables that lend insight into contextual variation of inequalities addresses key limitations of approaches that rely solely

on interaction effects to examine intersectionality, this approach faces its own limitations with respect to providing a flexible method sensitive to setting-specific configurations of inequality. 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). However, Model 3, like Model 1 and 2, is nevertheless fundamentally based on data measured exclusively at the individual unit of analysis. These models therefore ignore information that corresponds directly with contexts. As we will see below, a reliance on individual-level data carries with it a number of assumptions and limitations that may preclude the analysis of contextual variation in complex inequalities.

Model 4: Multilevel regression analysis where context is a second-order variable

A key assumption of conventional Ordinary Least Squares regression models that rely solely on an individual unit of analysis is that the errors (the 'e' term in equation 1.1, 1.2, and 2.1) associated with unexplained variation are similarly structured, that is independent or uncorrelated). However, this assumption is untenable wherever data is clustered in groups, whereby collective processes occurring at a higher level of analysis shape relationships between independent and dependent variables occurring at an individual level. Specifically, when contextual effects remain un-modeled as such, they are pooled in the regression error term, e, and the researcher or policy analyst is ignoring the fact that individuals who belong to the same schools, neighborhoods, labour markets, occupations and other groups may have correlated errors, and therefore violating a basic assumption of multiple regression (Luke 2004, pg. 7). In order to relax this independence assumption and incorporate contextual information directly into a single model, taking us beyond the capacity of Model 3, Model 4 is based on multilevel modeling.

A multilevel model uses a system of equations that predicts values of an outcome variable as a function of explanatory variables for individual characteristics and explanatory variables for collective level characteristics, making it fundamentally different from simple multiple regression analyses which do not employ context as unit of analysis. A system of equations (Luke 2004:10) with one collective level is described by the following equation.

Equation 4.1

$$\text{Level 1: } Y = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$$

$$\begin{aligned} \text{Level 2: } \beta_{0j} &= \gamma_{00} + \gamma_{01}W_j + u_{0j} \\ \beta_{1j} &= \gamma_{10} + \gamma_{11}W_j + u_{1j} \end{aligned}$$

Level 1 is the same as a simple regression equation except for the subscripts, where j tells us that a different level 1 equation is being estimated for every group at level 2, namely for every j -level unit. For example, if level 2 comprised cities and Y denoted wages, then a separate earnings average (represented by β_{0j}) would be calculated for the population of cities. Furthermore, if X denoted education, then a separate education differential or slope (β_{1j}) would be calculated for each city. At level 2 in equation 4.1, we can see how variation in cities shapes wage differences on an individual level, because both β_{0j} and β_{1j} become regression outcomes themselves at this higher level of analysis.

The core strength of multilevel modeling, in a technical sense, 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. This can be seen in equation 4.2 (Luke 2004:10), which simply combines the level 1 and level 2 parts of equation 4.1 through substitution:

Equation 4.2

$$Y_{ij} = \underbrace{[\gamma_{00} + \gamma_{10}X_{ij}]}_{\text{fixed}} + \underbrace{[\gamma_{01}W_j + \gamma_{11}W_jX_{ij}]}_{\text{random}} + [u_{0j} + u_{1j}X_{ij} + r_{ij}]$$

Thus, if we had a good theoretical reason for believing, for example, that indicators of post-industrial economic restructuring such as growth in services should impact wage differences on a collective level over and above educational attainment on an individual level (see McCall 2001), we can include service growth as a level 2 variable, represented in equation 4.2 by W . Here, γ_{00} tells us the overall wage average while controlling for city-level service growth and γ_{01} denotes the impact of service growth (W_j), and γ_{10} tells us the education wage differential while controlling for service growth and γ_{11} represents a cross-level interaction or multiplicative, multi-scalar impact of education and service growth on wages. Such an interaction may be significant if the impact of educational attainment on wage differences systematically differed between cities with high service growth and cities

with low service growth. That the slope for education and intercept or overall wage average are allowed to vary is confirmed by the models random effects (u and r) that denote sources of variation that are unaccounted for by the model (for information on how to evaluate a multilevel model see Luke 2004). In sum, interactions in Model 4 not only become more than a residual term as they often are in a simple multiple regression model, interactive relationships involving context itself become variables whose analysis contributes to our understanding of complex inequalities.

For an illustrative example, building on the first example in Model 3 that looked at Black and Veenstra's cross-contextual comparison study of self-reported health outcomes in Toronto and New York City, consider their findings with respect to the impact of neighborhood context. The authors were able to determine that neighbourhood-level income in these two cities had a significant effect on health outcomes, with higher incomes leading to greater odds of reporting good health, over and above the significant individual level effects of age, gender, nativity, race and class (Black and Veenstra 2001:85). Furthermore, by modeling the slopes of these individual variables they showed significant variation in individual level effects across contexts (shown in Table 4) in the case of New York City (in Toronto no such variation proved significant). Specifically, the health premium of identifying as White differed across neighbourhoods in NYC, as did the health penalty associated with the lowest income category.

An Example of Significant Cross-Contextual Variation in Multilevel Modeling

	Odds Ratio	
	Toronto	NYC
<i>Do slope coefficients differ significantly among neighbourhoods?</i>		
For gender?	-	-
For White versus non-White?	-	Yes
For lowest household income category versus the rest?	-	Yes
For having the lowest educational attainment versus having a high school diploma or higher?	-	-

(Source: Extract from Jennifer Black and Gerry Veenstra, pg. 86, 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,” in *Health Inequities in Canada: Intersectional Frameworks and Practices*, edited by Olena Hankivsky, & Sarah De Leeuw, UBC Press.)

Empirical findings 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 (Models 1 and 2), or as a function of average differences in a small number of groups (Model 3), but also in some cases across a population of group units (Model 4). By offering the researcher a tool to simultaneously investigate such higher-order effects alongside conventional individual-level relationships, multilevel modeling yields a powerful, context-sensitive approach to intersectionality that supports a more heuristic exploration of what dimensions of inequality are operating in particular circumstances. As such, we believe it represents the most advanced strategy in the intersectionality researcher’s quantitative toolkit.

Still, Model 4 is not without its own limitations, foremost among them its 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 units included in the analysis. This constraint on multilevel analysis often necessitates access to confidential microdata files located in Canadian Research Data Centres for high quality, nationally representative surveys. Moreover, applying multilevel modeling to complex survey data is a relatively recent and therefore underdeveloped practice that may not in every case lead to more robust inferences than convention models, suggesting these models may not always appropriate and a need for cautious application. Sufficient sample sizes pose a further challenge for Model 4, which as we saw also applies to Model 3 and, to a lesser extent Model 2. Model 3, as the case of Gunderson and Krashinsky’s analysis suggests, requires large sample sizes spread across group categories for questions that may have only recently been asked on nationally representative surveys. The three-way interaction effects of concern in Model 2 also require large sample sizes to ensure sufficient numbers of respondents in subcategories for questions that, similarly, may only recently have made it onto broad-based questionnaires (e.g. sexuality and fine-grained information on ethnocultural identity). Therefore, an increased capacity to conduct heuristic, and context-sensitive intersectional

analysis comes with increasingly onerous data requirements. This suggests that the most appropriate quantitative tool for any given analysis will reflect potentially competing concerns related to theory, data availability and analytical logistics (e.g. access to software and associated technical information).

Conclusion

Research which integrates an intersectional approach not only advances a deeper understanding of HRSDC's client populations but also serves to enrich the GBA+ lens used by the department, moving beyond limited conceptions of diversity to capture a more robust picture of the issues and challenges facing Canadians. The four models outlined here for examining complex inequalities respond to specific criteria for assessing the capacity and adequacy of regression models for intersectional analysis. Each model contains strengths and limitations in terms of conceptualizing intersectionality as well as logistical considerations. However, they are organized such that by moving from the first to the fourth, researchers gain greater insight into the social and spatial context of complex inequalities related to gender, race and ethnicity, class, age and other variables of importance to intersectional analysis. Attention to context, or specific configurations of inequality that tend to vary across time and space, forms one of three criteria identified as relevant when comparing approaches to a quantitative intersectional analysis. A second criterion is adopting a heuristic approach when deciding what variables to include in a given study of intersectionality. Such an approach contrasts sharply with analyses that treat the inclusion of particular variables as *a priori* or as simply assumed, rather than as a hypothesis or point of concern to be determined in part by the analysis. Importantly, contextual insight and a heuristic approach are intertwined and mutually reinforcing; by moving towards one, researchers move towards the other. This document has detailed the conceptual and methodological steps required to move towards a quantitative analysis of complex inequalities that pays greater attention to contextual specificity and simultaneously creates a stronger basis for heuristic intersectional research. The third criterion for assessing the adequacy of quantitative approaches to intersectional analysis involves decisions about the degree to which intersectionality is operating in the structuring of inequality. This varies in the models we have discussed from the more minimal operation in Model 1 to a more fulsome presence in Model 4.

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