Report on Faculty Salary Anomalies by Race and Indigenous Identity

Prepared by the 2023-2024 University of Waterloo Faculty Salary Anomaly Working Group (SAWG)

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Executive Summary

Introduction

This report presents the findings of the Salary Anomaly Working Group (SAWG) which was tasked to use data from the Equity Survey to investigate potential race-based and Indigenous-based salary gaps at the University of Waterloo, following the 2021-2024 Salary Settlement. The report begins with an overview of the mandate and membership of SAWG and the context in which the report is written. In the subsequent sections, we describe the data used for the analysis, the methodological approach to investigating salary gaps, and the results. The analysis was complicated by several conceptual and methodological challenges which we highlight throughout the report, and which illuminate potential avenues that may assist in UW's goals to continue identifying and addressing identity-based gaps in future analyses.

Background & Methodology

In writing this report, the SAWG was guided by the 2021-2024 Salary Settlement, previous reports, UW's salary structure, consultations with stakeholder units and feedback from faculty members, as well as methodological practices from the applicable literatures. Like the two most recent previous reports, this report employs regression analysis to identify group-based salary differences after controlling for work-related characteristics. This report provides additional analysis important to understand and address the methodological challenges specific to the investigation of identity-based gaps.

Main results

Investigation of potential race-based and Indigenous-based salary inequities involves substantially greater complexities and data constraints than analysis of sex-based gaps. Therefore, we begin this section by noting a few data and methodological issues:

- There is a lot of variability in the salaries of the identity-based groups (some have much lower salaries than the average, while others have higher than the average), resulting in very large standard errors in the regressions.
- Many identity groups have only a small number of respondents (e.g. 5, 15, and 19 are among our smaller group sizes). Hence the estimated gap could vary considerably with very minor changes in faculty complement.
- Information on racial identity and Indigenous identity is missing for approximately 35% of our faculty members. If the missing information is correlated with the faculty member's identity and with salaries, then the missingness could impact the estimated salary gaps.
- Concerns have been raised that by controlling for factors that themselves may contain bias could lead to hidden inequities in our salary model.

Therefore, subsequent to discussing the primary regression results, we provide additional analysis to shed light on some of the implications of these data and methodological complications.

In the primary regression analysis, we report that the estimated salary gaps for most identity groups are rather small or positive—more precisely, between -800 and 2200, where a negative gap means that the group's average salary is lower than the reference group after controlling for work-related characteristics. However, four groups have estimated average salary gaps that range between -2100 and -4200, namely: Black, Latine, Mixed, and Indigenous from Canada.

Because of the data and statistical concerns noted earlier (e.g. variability, small group sizes, missing information on identity, and potentially biased control factors), we conducted further analysis to assess these concerns. We report that results are similar whether we retain or drop observations with missing values, that we observe differences in work-related factors along racial lines, and that estimated salary gaps exhibit high variability with small changes in faculty complement.

In sum, we report that after controlling for work-related characteristics, the estimated salary gap for four identity groups is large and negative; however, the standard errors on these estimates are quite high and the data has notable limitations (e.g. missing information and small group size), such that we may be over- or under-estimating any potential systemic inequity (as highlighted in our analysis and examples).

Recommendations

Recommendations regarding potential adjustments

Because of the complexities highlighted throughout this report, the SAWG members have differing opinions as to which course of action is most appropriate: making salary adjustments versus not making salary adjustments. In particular, we do not have consensus on what constitutes reasonable criteria for identification of systemic gaps. The SAWG members are in consensus that a size criterion such as the one used in the 2020-2021 analysis is appropriate and that the estimated coefficients on Indigenous, Black, Latine and Mixed Race meet that criteria in that they all exceed 1% of median salary in 2020. However, the SAWG members are not in consensus on what the remaining criteria should be. Indigenous-based and race-based analysis are complicated by several factors, including (but not limited to) small sample size and the non-binary nature of race. While the previous (gender-based) analysis used p-values as a criterion to decide whether to make an adjustment, because there are few members of Indigenous and racialized groups there is a smaller likelihood of low p-values. Therefore, setting low p-values as a criterion for making adjustments could be seen as a systemic barrier to correcting Indigenous or race-based gaps. Moreover, there are further complexities with respect to how the analysis is conducted in terms of granularity. For example, if a minimum group size is required to conclude that a gap was identified, but at the same time members of racialized groups prefer to be defined in a more granular way, this could cause many groups to never meet the requirements to be considered for a group-based correction. The non-binary nature of race also complicates the decision-making because there may be both positive and negative gaps relative to the base group, therefore the decision is complicated by whether only negative gaps should be corrected, or whether the base group should also be given an adjustment in the case of positive gaps (e.g. some racialized groups earning more than the base group). We hope this discussion provides useful information to the Provost and FAUW President in making their decisions regarding the terms of the 2021-2024 Memorandum of Salary Settlement.

Recommendations for Future Work

While the SAWG was not able to reach consensus on the most appropriate course of action regarding salary adjustments, the group was in agreement on several secondary recommendations. We believe that the following (in no particular order) might assist in improving UW's ability to evaluate and address identity-based gaps:

- Further evaluation and monitoring of internal assessment processes and other inputs to salary (upstream factors), including Merit Scores, OPAs, Rank and Starting Salaries.
- Continued improvement in data collection (use of Workday data), and consultation
- Analysis of additional groups (e.g. accounting for disability, gender identity, and additional dimensions)
- Collection and analysis of data across time
- Tracking chronic anomalies
- Exploration of interactions
- Review by relevant stakeholders of the identity groups used for salary anomaly analysis.

Contents

1. Introduction

This report documents the work of the 2023–24 Salary Anomaly Working Group (SAWG) and presents the findings of the Working Group's investigation which updates the results of the 2021 Salary Anomaly Review to identify any potential group-based anomalies/inequities (henceforth referred to as gaps) based on race or Indigeneity at the University of Waterloo (UW).

The scope of the present report follows the mandate provided by the 2021-2024 Salary Settlement, which was to investigate all cases where race-based and Indigenous-based salary gaps may exist. In conducting this investigation, the SAWG has been guided by previous reports, UW's salary structure, consultations with stakeholder units on campus, feedback from faculty members, and methodological practices from the applicable literatures.

We note that the analysis faced several conceptual and methodological challenges, which we discuss in this report. These challenges have helped to illuminate several potential avenues that could assist in improving UW's ability to identify and address identity-based gaps in the future.

In the following sub-sections of this introduction, we present the mandate and membership of SAWG, describe the aspects of the UW context that are important for understanding how faculty salaries are determined, and describe the consultations that the SAWG undertook with various stakeholders at UW. In Section 2, we describe the equity survey data that were collected at UW, including their limitations. In Section 3, we describe the specific dataset that we used for our analyses and Section 4 describes our approach to identifying salary gaps and the specific models we used.

The results of our analyses are presented in several sections. Section 5 presents relevant descriptive statistics and Section 6 presents the results of regression models identifying potential race-based salary gaps. In Section 7, we present the results of an analysis of some of the model's explanatory factors, including merit scores, academic rank and the receipt of Outstanding Performance Awards, which potentially contribute to some of the observed salary differences. In Section 8 we discuss and interpret our results, and we present recommendations in Section 9.

There are several appendices to this report. In addition to detailed information on the equity data and the variables used in our analyses, we include several sensitivity analyses that help us understand the degree of variability around our estimates of salary gaps. In particular, we illustrate the potential effects of small sample size by examining the results of some hypothetical changes to the size and racial composition of the sample.

1.1 Background: The 2021-2024 Salary Settlement and the Formation of the current Salary Anomaly Working Group

The 2021-2024 Salary Settlement included the following text:

> The University is currently developing an equity data collection strategy for all students, faculty, and staff, to further its commitment to addressing systemic racism within the university. Development of this strategy includes consultations with stakeholders that will inform appropriate use of data and potential limitations of use. The University agrees to a target date of the end of 2021 for initiating disaggregated data collection on faculty members' race and Indigeneity.

> As soon as responses are available and processed for at least two-thirds of FAUW members, the University will provide the raw disaggregated data on race and Indigeneity to the Salary Anomaly Working Group, who will use it to update the results of the 2021 Salary Anomaly Review to identify any race- based anomalies. If race-based anomalies are identified, they will be resolved and compensation will be retroactive to May 1, 2021.
>
> The University remains committed to a five-year cyclical review of faculty salary anomalies that works to identify both individual as well as systemic salary anomalies, as agreed in a Joint Provostial-FAUW MoA executed on February 26, 2015. For the review that will begin in 2025, the University will broaden the original mandate of the Salary Anomaly Working Group to include the addition in bold:
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> *"investigate all cases where faculty salary inequities, including but not limited to gender-based,* **racialized, and Indigenous** *inequities, may exist and recommend how such cases should be resolved using the Faculties' existing anomaly funds; review the processes by which salary anomalies are currently identified and resolved in each Faculty; establish a standardized university-wide process for the detection and resolution of all faculty salary anomalies that may arise in the future, wherever they may occur."*

As a result of this settlement, in February 2023 a new Salary Anomaly Working Group (SAWG) was formed with three members appointed by the Provost, and three members appointed by FAUW.[1] The Provost appointees are Christiane Lemieux (Statistics and Actuarial Science, co-chair), Martin Cooke (Sociology and Legal Studies & School of Public Health Sciences) and Changbao Wu (Statistics and Actuarial Science), and the FAUW appointees are Kate Rybczynski (Economics, co-chair), Rashmee Singh (Sociology and Legal Studies) and Michael Wallace (Statistics and Actuarial Science).

As stated in the Salary Settlement, the mandate given to the current group is to "update the results of the 2021 Salary Anomaly Review to identify any race-based anomalies." It goes on to say that "If race-based anomalies are identified, they will be resolved, and compensation will be retroactive to May 1, 2021." The text also indicates that this exercise is to be done using the responses from the equity survey data (more information on this survey is provided in Section 2) as soon as the response rate for FAUW members meets or exceeds two-thirds.

Three additional clarifications are in order. First our interpretation of the reference to race-based anomalies is that it is meant to also encompass anomalies based on Indigeneity, given the full text in the second paragraph of Section 5 of the MoA.

Second, we understood the mandate to "identify any race-based anomalies" to mean identifying specific racial or Indigenous identity categories associated with salaries that are systematically lower than some reference. This is to say that our mandate was to identify group-based salary gaps, not individual faculty members whose salaries might be anomalous.

Third, the group co-chairs clarified with the Provost and President of FAUW that the group's work was limited to analyzing the data. If "race-based anomalies" i.e., group-based salary gaps based on racial or

[1] FAUW's appointments followed an open invitation to members to volunteer, from which three were selected.

Indigenous identity, were found, the decision of how to resolve them lies with the Provost and President of FAUW.

1.2 Salary Structure at UW

In this section we provide an overview of salary structure at UW, as this information helps to inform the analysis in this report.

Faculty members' salary growth is determined by several factors. First, the starting salary (at hiring) forms the initial base salary. Then, every year, that base salary is increased according to a defined process. The factors that contribute to base salary increases[2] are:

a) scale,
b) relative merit,
c) outstanding performance awards (OPAs),
d) salary thresholds, and
e) anomalies and other discretionary salary adjustments.

Specifically, each year a faculty member's base salary increases by a fixed percent (scale), plus a selective increase based on their R (merit) score relative to the average R of their faculty – (adjusted by where their salaries are in the threshold system), plus any anomaly, OPA, or discretionary increase. An anomaly adjustment would be added if a salary was identified as anomalously low; discretionary increases may be applied based on market factors such as competitive outside offers. We note that upon promotion to a higher rank, if a member's salary were below the floor for that rank, they would obtain a floor-based salary increase; however, analysis of the data shows that faculty members salaries are all several thousands of dollars above the floors within each rank and have been so as far back as we have data. Thus, rank-based floors are not currently affecting our salaries.

This information on salary structure informed the decisions regarding the factors that were important to include in this analysis. It also indicates that salaries at Waterloo are formed in a highly deterministic manner, mainly by annual scale increase, and selective increases (merit scores and OPAs), as described in the MoA, and that one of the most important factors potentially leading to anomalies is therefore starting salary. For the interested reader, please refer to Appendix A.4 for a detailed description of how salary increases are determined.

1.3. Previous reports

As noted in the introduction, this analysis was informed by previous SAWG analyses. There have been a handful previous salary analyses conducted at UW. Here we focus on the two most recent ones.

The 2015/2016 review used regression analysis[3] to detect individual anomalies and to estimate any gender-based salary gap. Based on this regression model, it determined that female faculty members earned on average $2,905 less than their male counterparts, after controlling for many characteristics such

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[2] Note that leaves and administrative/research stipends also influence faculty members' annual salaries; however, these factors are not permanent – they do not increase the base salary and are therefore not part of this analysis.
[3] More information on how regression analysis is used to study salary anomalies/gaps is provided in Section 5.2.

as rank, years at UW, academic group[4], average merit scores, and number of OPAs. The full list of factors is provided in Appendix A.2. This analysis led to a corresponding salary correction for all female faculty members in the bargaining unit as of April 30, 2015, effective as of September 1, 2016.

The Salary Anomaly Working Group that conducted the 2020/2021 review opted to keep a very similar regression model as the previous group but made some changes to the academic groups after consultation with the Deans and after performing a statistical analysis of starting salaries by academic group. The main change was to group the Department of Psychology with the rest of the Faculty of Arts. The Working Group then tested for a gender-based salary gap using a similar approach to that of 2015/2016. They found that female faculty members earned, on average, $37.31 less than their male counterparts, after controlling for the noted characteristics. Based on these results, no salary adjustment was made.

1.4. Consultations

At the start of the process, the co-Chairs of the SAWG consulted with various units on campus. The purposes of these consultations were to help the group understand the data that were to be used and to identify any especially salient factors that should be considered in the analyses. We consulted with IAP, the Office of Indigenous Relations, the Equity Unit and the Anti-Racism Unit of the Office of Equity, Diversity, Inclusion and Anti-Racism, and the Faculty Association's Equity Committee. We also heard from faculty members who directly reached out to members of our Group. These consultations have provided important guidance and informed both the methodological and data decisions made within this report. We summarize here some of the main themes pertaining to the SAWG analysis that were raised during these consultations, and which were further discussed by our Group:

- **Rank** – Concerns were raised that racialized faculty are more likely to be concentrated in lecturer rank. A similar note was raised around sex-at-birth, that female faculty were concentrated in ranks below full professor. Concerns were raised about whether models which control for rank are appropriate if rank itself is not free of inequities.

- **Merit** – There is a perception that lecturers receive lower merit scores, on average, than other ranks. Again, a similar issue was raised in the analysis using sex-at-birth. More generally, there is a concern about whether the merit process is itself biased and therefore whether or not this measure should be used in the model, as well as how estimated gaps should be interpreted when the model does include variables like merit or rank if these variables themselves are not free of biases.

- **Race Identifiers** – Concerns were discussed about the validity of race identifiers in the survey. As "race" is a social construct, ideas about racial categories are extremely variable. This variability can exist historically, across contexts, between individuals, and even within the same individual across time. For example, faculty members with similar backgrounds might have very different perceptions of groups, or might not identify as belonging to any constructed racial categories at all.

[4] Academic groups are groupings of departments/schools within Faculties for which salaries are observed to be markedly different, potentially due to market premia for those disciplines. Some of these groups encompass entire Faculties (Health, Environment), some correspond to specific departments/schools with salaries deemed different enough from the rest of their Faculty (School of Accounting and Finance, School of Computer Science, School of Pharmacy, etc.) and the remaining groups are the rest of these Faculties after removing these departments/schools (e.g., Faculty of Mathematics faculty outside of the Cheriton School of Computer Science). Details are given in Appendix A.2.

- **Disability** – There was interest in expanding the scope of future analyses to consider disability as well. In this context, the issue of invisible versus visible disability, as well as onset and timing of disability, were highlighted as potentially important factors.

- **Intersectionality** – A question was posed as to whether the working group would be looking at intersectionality, both in terms of the control factors, as well as the identity markers. For example, would the analysis consider the impact of rank by race identifiers, and would the analysis consider the intersection of race and disability or sex-at-birth?

- **Timing of Hire** – Faculty members noted that while it is not necessarily relevant for the current analysis given that the data are from 2020, future Salary Anomalies should consider that cluster hires for Black and Indigenous scholars may have very different (larger) starting salaries than previous cohorts.

- **Confidence in the Data** – Concerns were raised over how confident we are in the data, and whether a sufficient number of faculty members participated.

- **Verification** – The question of verification of racial or Indigenous identity was raised.

- **Starting Salaries and Causal factors** – Concerns were raised over how the causes of the gaps were being interpreted and, in particular, whether all was being chalked up to starting salaries and was therefore "fixable" with a simple adjustment. Noting that the reasons for the gaps were important, faculty members have requested an investigation of starting salaries, among other potential sources of systemic bias.

- **Chronic Anomalies** – Faculty members questioned whether certain groups were more likely to be chronically experiencing anomalously low salaries and suggested that chronic anomalies be further investigated for group-based inequities.

- **Clarifying Methods** – Faculty members asked for clarification on how our analysis would identify salary inequities, and more broadly how salaries are determined at UW. Faculty members asked for more clarity in the report, in order to better understand how to interpret the results.

The Salary Anomaly Working Group is grateful to the community for bringing and discussing these important and relevant concerns. We discuss the theoretical and empirical tools that we use to investigate these concerns in the analysis below, including references to how similar equity-based salary studies approached these issues.[5]

Additionally, faculty members proposed that the Salary Anomaly process also include the following.

- Information on how Deans will adjudicate cases and communicate corrections to faculty members.

- Provision of a calculator tool and guide to enable faculty members to better understand anomalies and how their individual salaries are affected.

[5] See Basri et al. (2015).

- Time the release of the Salary Anomaly report early enough to enable faculty members time to discuss with their deans prior to the salary increase process.

These last three concerns, as well as investigation of starting salaries, chronic anomalies, and timing of hire, fall beyond the capacity of our current working group, but we note these as concerns that might be addressed in the future.

2. Equity Data Collection at UW

The University of Waterloo currently has an Equity Data Strategy described in detail on a dedicated website. This website includes information about the 2021 Equity Survey that is to be used for this analysis as well as the "Equity Census", launched in Fall 2023, and which we expect will be used for future analyses. Rather than repeating the information found on this website, pertaining to the goals of this data collection and how it was designed, we instead highlight a few characteristics of the 2021 Equity Survey that are relevant to our analysis.

In general, the 2021 survey asked all UW employees, including faculty members, to identify themselves in terms of race, gender and sexual identity, Indigeneity, disability, and religion, among others. For ease of reference the full questionnaire is provided in Appendix A.1.

First, it is important to note that all answers are based on self-identification, and that for each question there is an option to choose "prefer-not-to-answer". Second, for the racial identity question, respondents could choose multiple responses, as well as a write-in response. Third, the Equity Survey data collection started in 2021 and, possibly because this is still a relatively new process for the UW community, the response rates for the survey were not very high. Finally, we wish to clarify that the Equity Survey is entirely separate from the ongoing Equity Census. A faculty member who responded to the Equity Survey would not have their information transferred from the Survey to the Census. To be counted in the census, a faculty member would, therefore, have to fill out their census information using the census input forms.

3. Data Set

3.1 General Overview of Our Data Set

The data used for this report consists of administrative data held by HR in Workday and by IAP, linked to equity data from the 2021 Equity Survey. The anonymized data set that was provided to us combined the data set used for the 2020-2021 Salary Anomaly Review, with salary data as of May 1, 2020, along with several work-related information, including corrections that were made, especially to the year of hire. All regular faculty members with appointments of a year or more as of May 1, 2020 were included in this data set. It was then augmented with a selected set of responses from the Equity Survey. These include the answers to Questions 1 (Disability), 2 (Gender Identity), 5, 5.1, 5.2 (Indigenous Identity and sub-questions for those who are Indigenous from Canada), and Question 6 (Racial Identity).

We note that while the Salary Settlement MoA did not mention explicitly that disability should be considered in this off-cycle salary anomaly review, the group requested this information for the purpose of studying interactions with racial and Indigenous identities. We acknowledge that disability is important to consider in and of itself for the assessment of salary anomalies. Gender identity is another important factor that we were unable to explore at this stage, although we believe that both dimensions should be fully integrated in future salary anomaly reviews. The Equity Survey questionnaire is provided in Appendix A.1. Appendix A.2 lists data fields used in the SAWG analysis.

3.2 Cohort and Data Collection Timeline

An important consideration for interpreting this analysis is the timing of the Equity Survey data collection relative to the salary data, as well as the length of time between the salary data and the analysis. We explain these issues below.

The salary data were collected as of May 2020, and were merged with the Equity Survey Data, for which data collection began in July 2021, was paused in October 2021, and reopened for employees in May 2022. Because of the different collection times, there are some faculty members for whom we have salary data, but who had left the university before providing Equity Survey data. As such, some missing responses might have resulted from differences in the timing of the salary and the Equity Survey data. The group requested additional information on whether a faculty member left UW between these dates in order to check our interpretation of the different ways in which these non-responses were coded. We note here that our analysis was done on the same set of employees as the 2020-2021 Salary Anomaly review, that is all employees in the bargaining unit as of May 1, 2020, regardless of whether they are still employed by UW as of now. Also, because the group was tasked to investigate 2020 salary gaps, employees who answered the equity survey but were hired after May 1, 2020, are not part of this analysis. The timing of the equity data completion and preparation for the SAWG creates a large lag between the time stamp of the data and when the analysis is occurring, much longer than the usual one-year gap present in the regular salary anomaly reviews.

3.3 Missing Information

The Group received anonymized data for 1,311 faculty members. While we had complete salary information for each of these members, we did not have equity data for all members. One of the reasons for this missing information is due to the data collection timing issue described in Section 3.2.

However, there were several additional types of missing information which we had to address in our analysis, for example, survey nonresponse and non-response to specific survey items. The Equity Survey was a voluntary survey, distributed to all UW employees. Among those who answered the survey, some left some responses blank (“skipped” a question), as the survey software did not require a response to each question to be provided. We did not have full confidence that the encoding used in the data set accurately differentiated those who did not respond to the survey from those who responded but had skipped specific questions, as there were also some blank answers in the data set. Another reason that information is missing is that identity questions on the Equity Survey provided respondents the opportunity to indicate “prefer not to answer.”

We opted to treat those who did not answer the survey and those who appeared to have skipped a question as a single group. We refer to this comprehensive group as “No Answer”. The size of the “No Answer” group was 412 and 409 for the racial and Indigenous identity questions, respectively. For the remainder of this report we have combined this group with individuals who chose the answer “prefer not to answer” (referring to the combined group as “unknown”), because both groups contribute to generating missing data and differentiating them in terms of the mechanism by which it is missing would add complexity to our models that was deemed unnecessary because it did not alter the main findings.

3.4 Identity Categorization

Here we wish to address a few additional points regarding the data from the equity survey used in our analysis.

First, given that respondents were able to choose multiple answers for racial identity (we note that fewer than 15 respondents did so), in the analysis presented in Sections 5 to 7, we treat racial identity as a collection of indicator (binary) variables indicating whether or not a faculty member chose a given answer, as opposed to being a single variable with different mutually exclusive answers.[6] Indigenous identity is included as a separate indicator variable that equals one if an individual identifies as Indigenous from Canada, and zero otherwise. We note that Indigenous identity is entirely separate from racial identity, and this model can capture exactly how respondents chose to answer these two different sets of questions without making further assumptions or groupings.

Second, the data we had are static, in that we could only see a snapshot of the answers to the equity survey at the time where data was captured to be provided to our group. We did not have longitudinal data for members who transition from one identity to another or for whom a disability might have manifested, remained or resolved over time. Furthermore, and as pointed out in Section 3.2, the timing of this snapshot is such that it may not match a person's identity or status as of the time of the salary information draw (May 1, 2020).

3.5 Overall Concerns with Data Set

We conclude this section with a cautionary note regarding the data set. The relatively high non-response rate along with the fact that missing information is not due to a random selection process but rather due to self-selection, is introducing potential biases into the results. Furthermore, as will see in Section 5, many identity groups have relatively small numbers of respondents (fewer than 10). With such small groups a change in even one or two observations can result in markedly different estimated results, making the results for these groups vulnerable to missing information (e.g., see Appendix A.5). We conducted our analysis despite these caveats but we discuss their impact throughout the report.

4. Methodology

Our current Salary Anomaly Working Group has continued with the regression approach to investigate identity-based salary differentials. There is added complexity in this analysis for a number of reasons, including missing information and identity categorization as discussed above.

We use regression to estimate potential group-based salary gaps among faculty members. The identity groups we investigate are: identification as Indigenous from Canada, specific self-identified race categories, and sex-at-birth.[7] We were guided in employing these specific groups by the wording of the Memorandum of Salary Settlement (item 5) and the categories provided in the Equity survey.

Because there are several issues with both the data and the choice of model, we ran additional regressions to test whether the estimated results are sensitive to the data and modelling choices that we made (this

[6] This decision allows a more nuanced approach to concerns over the construct of racial categories as well as ethnicity, and is consistent with the direction being taken by the major North American statistical agencies.
[7] We retain sex-at-birth in the model, a data field that comes from Workday and not from the equity survey. We note further that intersectionality is also important, and while we would ideally include specific intersections with race and sex (and race and disability), we currently have too few faculty members in these intersections. As such, we take an additive approach by including these equity groups separately only (without interaction terms). Another benefit of this approach is that the results are then comparable to the 2020 model.

additional analysis is referred to as "sensitivity analysis"). In other words, regression models allowed us to assess how various factors affect salaries. By incorporating a sensitivity analysis, we could test the impact of different data and models choices (i.e., choices of factors) on the salary analysis. For example, in Appendix A.3 we test if the overall results of the model change when we use the smaller sample of faculty members for whom there is no missing information. However, the working group wishes to acknowledge that despite our best efforts and techniques, there are many technical concerns that remain with our analysis and interpretation of our results. We do our best to highlight these throughout.

4.1 Model(s)

For colleagues who appreciate visualizing the analysis using algebraic models, we present our primary model specification here.

The basic model to estimate salary gaps is:

$$\text{Annualized Salary}_{2020,\,i} = \beta_0 + \beta_1 F_i + \beta_2\, \text{IndigenousCanada}_i + \theta\ \text{Racial Identity Categories}_i + \lambda\ X_i + u_i$$

where,

Annualized Salary$_{2020,\,i}$: the faculty member's full-time full-load equivalent annual base salary (so for a faculty member working full-time full-load and not on leave with no stipends, Annualized Salary$_{2020,\,i}$ is their actual annual salary; for a faculty member working less than full-load Annualized Salary$_{2020,\,i}$ represents the amount that the faculty member would be making, at their current rate of pay, if they were working full-load)
F_i : an indicator that equals 1 if the reported sex-at-birth is female, and zero otherwise.
IndigenousCanada$_i$: an indicator that equals 1 if an individual has identified as Indigenous from Canada, and zero otherwise.
Racial Identity Categories$_i$: a vector of indicator variables representing each of the racial identity categories listed in the Equity Survey. e.g., Black, East Asian, and so forth (see Appendix A2 for full list). Note that an individual may select and be represented in more than one category. Such that an individual may have both Black=1 and Latine=1 should they so identify. Detailed information on the prevalence of responses, including multiple responses, is provided in Section 5.
X_i : a vector of work-related variables including, Academic Group, Years at UW, Years at UW squared, average merit (R) scores for the past 7 years, number of OPAs, rank, Lag (number of years between PhD and hire at UW), interactions between lecturer stream and Academic Unit, and Lag and Rank at Hire. That is, we use the same vector as the 2020 report as our starting point for comparability.

Referring to Section 1.2. on salary structure, we are accounting for the primary factors that enter our salaries algorithmically: Merit (R) scores, OPAs, and time at UW (which generates year over year increases due to scale). Academic Group is not in our salary structure directly; however, we note that Academic Group will affect starting salaries, and therefore the initial base from which our salaries differ.[8]

[8] We reiterate the important decision made in the 2015 report to exclude starting salaries from the model. Because of our highly algorithmic salary progression, starting salaries are likely to be THE major source of salary gaps at UW.

Rank enters our salary structure via the different thresholds for lecturers versus tenure-stream faculty, but is also expected to influence starting salaries for those hired at more senior ranks.[9]

The estimated coefficients on the identity categories represent estimates of the group-based salary gaps (after controlling for work-related characteristics). So for example, the female-male wage gap would be represented by β_1. For any indicator variable (e.g. the identity categories), the gap is estimated relative to the group or category that is omitted. For sex-at-birth categories, the group that is omitted is male. For the IndigenousCanada the group that is omitted is non-IndigenousCanada (this includes both non-Indigenous and Indigenous from Outside of Canada). For the race categories, the omitted group is faculty who selected only the "white" category and none other. We refer to this group as "white" from here on, with the understanding that this group does not include respondents who chose white and at least one other racial identity.

4.2. How the Regression Models Work to identify Salary Gaps

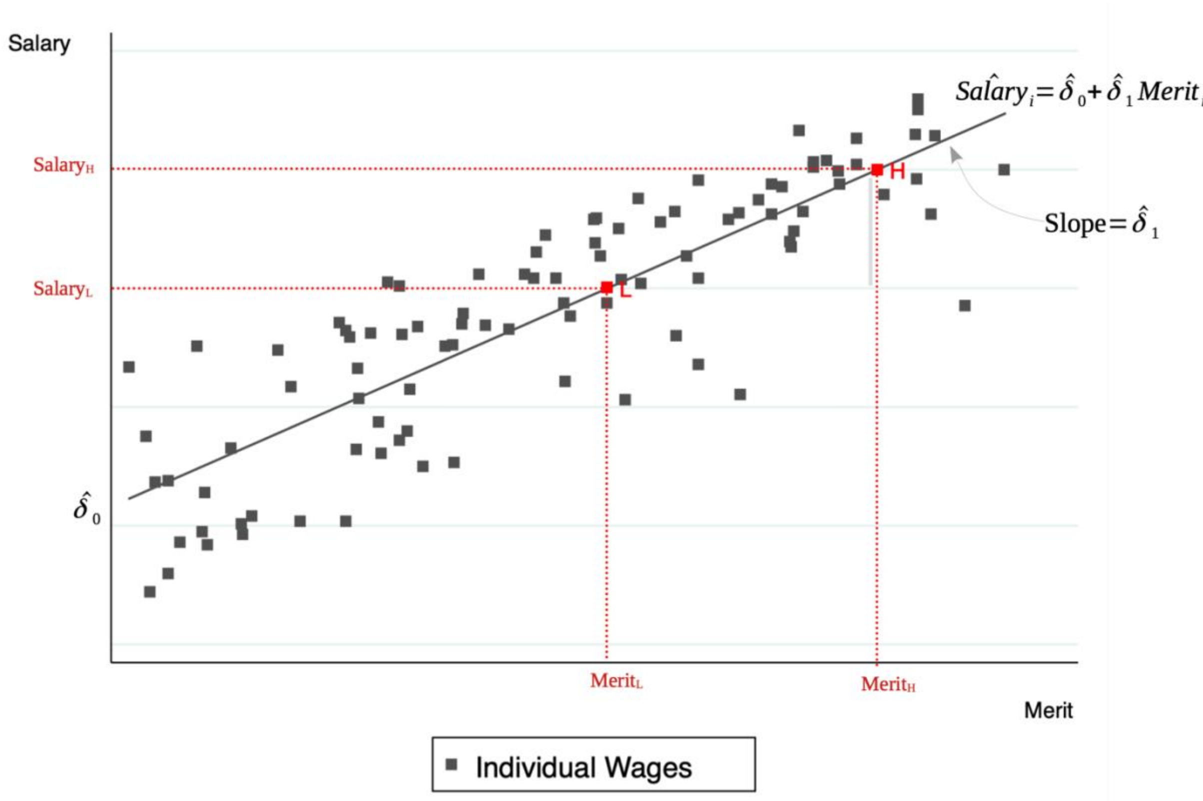
For faculty members not familiar with salary or wage gap analysis, we provide a brief explanation of how these models work. The regression model estimates the "effect"[10] of one or more characteristics on the outcome of interest. For example, a very simple model estimating the "effect" of Merit on Salary is:

$$Salary_i = \delta_0 + \delta_1 Merit_i + u_i$$

Estimation of this model tells us that for each unit increase in Merit, Salary is expected to rise by δ_1. Graphically, we are fitting a line to best reflect the relationship that we observe in the data, as shown in Figure 1. We then use this fitted line to show how much higher we expect salary to be for a person with higher merit (person H) versus a person with lower merit (person L). $Merit_H$ relative to $Merit_L$ yields an expected salary difference amount of $Salary_H$-$Salary_L$. This amount is considered to be an "explained" difference in salaries. And this explained difference in salaries is generally interpreted as a valid reason for differences in salaries; faculty with higher merit should be earning higher salaries. (Please note that the "data" in this example are randomly generated, and are used as an example. This is not actual faculty salary data and does not resemble actual salary distributions.)

[9] Rank is one of the more contentious variables in salary equity studies, and we explain why in Section 5.2 of this report.
[10] We use the term "effect" loosely here. We are not applying a causal interpretation because there are too many issues with the analysis for this to be reasonable. For example, we expect substantial selection bias issues which may very likely be correlated with identity categories. (Who remains in the UW faculty member population may depend on their salaries and outside offers).

Figure 1: Graphical depiction of a simple regression model explaining differences in salary based on merit differences



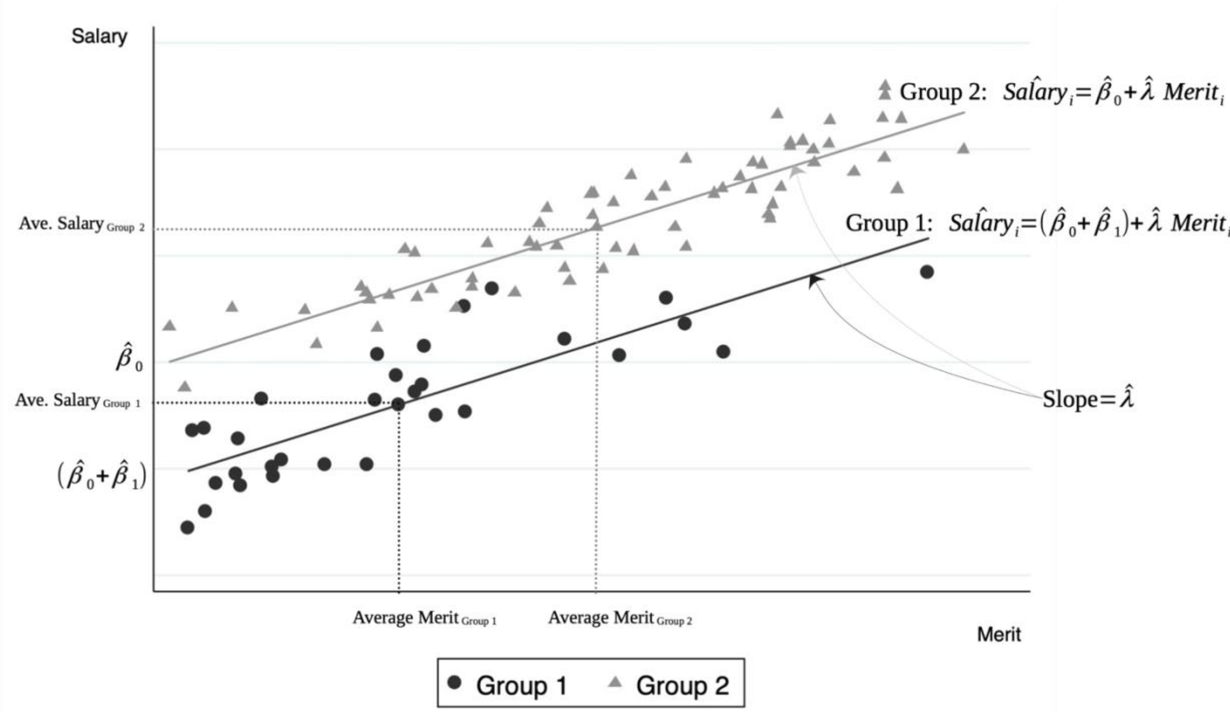
But of course, the purpose of our work is to investigate the presence of group-based salary inequities. So how do we do that within this context? Continuing with this simple example, we add a group-based identity indicator variable, I. Lets say we are comparing group 1 to group 2, and we estimate the model

$$Salary_i = \beta_0 + \beta_1 I_i + \lambda\ Merit_i + u_i$$

and obtain a negative estimate for $\hat{\beta}_1$.

What the model does is estimate the effect of Merit on Salary, and after subtracting that "explained" Merit effect out for every observation, the difference that remains between group 1 and group 2 is considered the "unexplained" salary gap. Predicted salaries for group 1 and group 2 in this model can be visualized as two separate lines with the same slope, and the difference between the lines is $\hat{\beta}_1$ which is the estimated coefficient on the identity marker, I.

Figure 2: Graphical depiction of a simple regression model explaining salaries across two identity groups

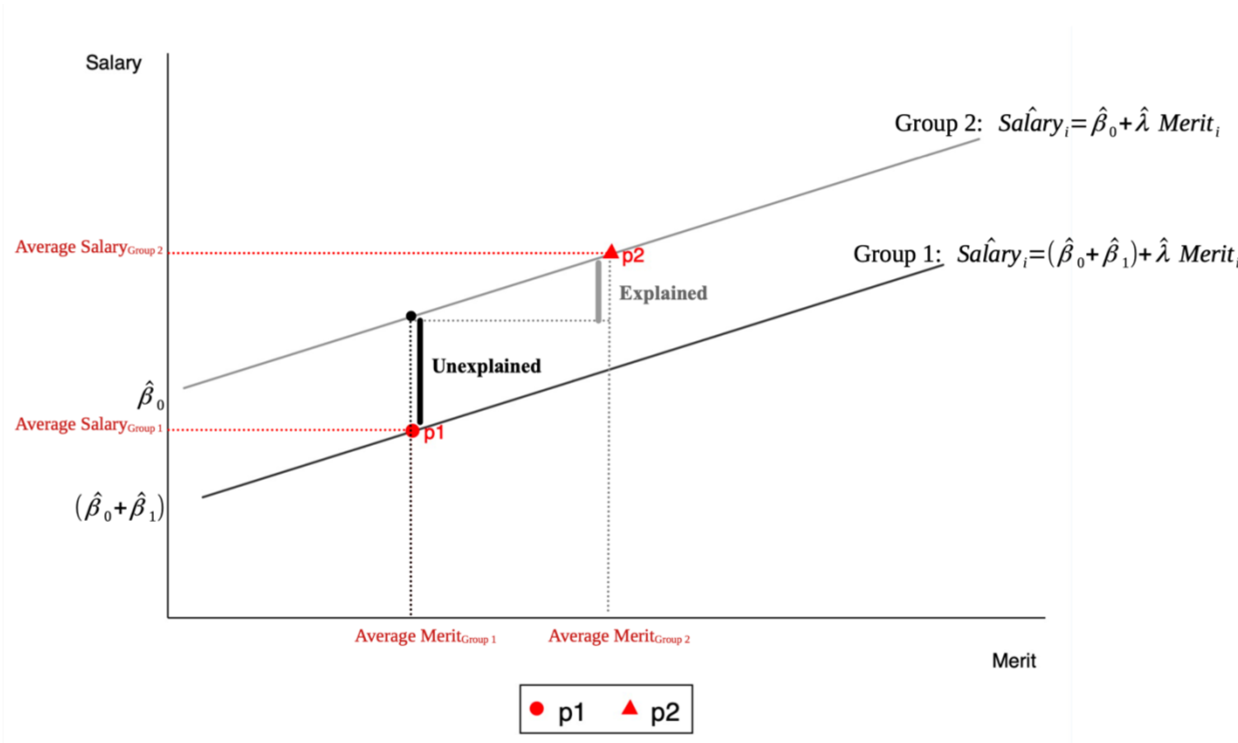


So, in essence, what this analysis does, is separate the part of the salary gaps that we can't explain from the part that we can explain. What we can't explain is the difference between the groups (that is why, after controlling for the appropriate characteristics, we still obtain an estimated salary effect of belonging to an identity group, $\hat{\beta}_1$). This distance is depicted by the black bar (Unexplained) in Figure 3. The part of the total salary difference that is considered explained is the part attributable to higher levels of the relevant characteristic. That is the vertical rise that would be obtained by increasing merit from Average $\text{Merit}_{\text{Group 1}}$ to Average $\text{Merit}_{\text{Group 2}}$. This distance is depicted by the grey bar (Explained) in Figure 3.[11]

We depict the Explained and Unexplained components in Figure 3, below. This graph is the same as in Figure 2, but the individual data points have been removed for a tidier picture.

[11] The unexplained gap is calculated by taking the coefficient on the characteristic (lambda hat) and multiplying it by the difference in the average merit scores by group.

Figure 3: Decomposing salary differences into Explained and Unexplained components



The "unexplained" part is often interpreted as capturing the salary inequities.[12]

However, it is important to note that inequities can enter our salaries via these "explained" factors as well. For example, subconscious biases may not only affect salaries directly, but also the factors that determine salaries such as the merit process. This concern is particularly important as salary increases are highly algorithmic, and because merit plays a role in that algorithm.

This concern has been raised by some faculty members – what if there are biases in the explanatory variables themselves? Would that not lead to incorrect estimates of the identity-based salary inequities? The answer is yes, it could, because the analysis would then in essence "explain" salary differences based on a characteristic that, itself, may contain unexplained gaps. This concern has been widely noted in the wage gap literature.[13] Aptly put by Baker and Drolet (2010) in the context of gender,

> [t]here is some debate over which explanatory variables can be legitimately included in this regression. Occupation provides a nice demonstration of the issues, although the argument could apply in principle to many characteristics. Some people believe that differences in occupation across the genders are the result of differences in preferences between males and females, and so there is little reason not to include

[12] Sometimes referred to as the "discrimination" component. This interpretation is problematic, however, if we have selection bias or other data and modelling issues. For example, if we are unable to include the full set of characteristics that influence salary outcomes that are also correlated with our identity markers, then our estimators of the salary gaps may be biased upward or downward.

[13] See, for example, Baker & Drolet (2010) p.447, Borjas (2013) p.390 and Basri et al. (2015) p.47.

> them in the decomposition. Other people believe that women are forced into certain occupations and/or denied access to others, so that gender differences in occupation are in fact a measure of the discrimination females face in the educational system and in hiring. In this case, including occupation in the regression runs the risk of explaining discrimination with discrimination. Rather than taking a strong stand on this issue, we offer decompositions of the log wage gap using both specifications. (Baker and Drolet, 2010).

In the context of faculty salary studies, Basri et al. (2015) also point to this debate in that 'rank variables are what statisticians would call "tainted."' Rank, like salary is under the employer's control. If salary decisions reflect bias, then rank decisions would, it is argued, probably also reflect that same bias. Thus, some would conclude, rank variables should not be used in studies of salary equity, particularly if the studies also control for experience."

The Salary Anomaly Working group has worked to ensure that we are transparent about these potential avenues of bias. Moreover, we conduct sensitivity analysis and present simple descriptive analyses in order to assess these potential avenues of bias in the estimated salary gaps. See Section 7 and Appendix A.3.

4.3 P-values discussion

Frequently empirical research reports p-values, sometimes used as thresholds for "statistical significance", alongside coefficient estimates. What are p-values? A p-value represents a probability. Under certain conditions, the p-value represents the probability of observing data which would elicit a coefficient at least as large in magnitude as that actually observed if the null hypothesis were true (the null hypothesis is that the true population parameter is zero).

The difficulty is that many of the conditions that we require to calculate a correct probability (a correct p-value) are unlikely to be true in our analysis. For example, among the conditions we assume are: random sampling and normal distribution of the residuals (estimated errors). In practice, these frequently do not hold, nor do they hold in our specific case. When the assumptions underlying our statistics are not satisfied, then our conclusions are no longer reliable.

Another issue to consider is that p-values are used in the context of estimating relationships based on a sample drawn from a larger population (so that we may draw inferences from the sample and apply these to the population as a whole). While we have non-response in some variates, this study is conducted using the entire population of UW faculty members, which raises the question of whether p-values are meaningful here.

Finally, we note that p-values are more likely to be lower when the number of observations is larger, thereby making low p-values less prevalent under small group sizes.

It might be helpful to note here that p-values for coefficient estimates are based on t-ratios. These t-ratios are constructed by dividing the coefficient estimate by the standard error of the coefficient estimate. So, while p-values may not represent reliable probability conclusions, the components they are based on can be informative. Specifically, the standard error of the coefficient estimate gives us a sense of the variation in the estimated relationship between the identity marker and the salary. Larger standard errors represent greater variation.

We opted to report both the standard errors and the p-values. The standard errors, when contrasted with the coefficient estimate, give a sense of the wide variation in the estimated relationship. That is, larger standard errors may indicate that even a small change in the underlying data could elicit a large change in the coefficient estimate, something we will stress again in Section 7 and explore in Appendix A.5. On the other hand, the p-values apply a probability to the ratio of the coefficient to the standard error. We hope that our colleagues find this useful in assessing the reported results.

5. Descriptive Statistics.

In this section we report quantitative summaries describing the composition of our data set in terms of racial and Indigenous identity answers as collected in the equity survey data, as well as the sex-at-birth variable collected in Workday. We also provide descriptive statistics for a few of the explanatory variables entering the salary model described in the previous section.

5.1 Counts by Identity Group

Tables 5.1 and 5.2 present counts of faculty members who identified with each of the Racial & Indigenous Identification groups in the Equity Survey.

We note that out of the 1,311 individuals in our data set, 412 did not answer the question about racial identity (either did not answer the survey or skipped the question) and 50 chose prefer-not-to-answer, representing a total of 462 individuals for whom racial identity was unknown. While most respondents chose only one answer, some individuals chose between two and four answers. This is why the total number of answers was 1,317 instead of 1,311. Group sizes with fewer than five respondents are not shown but are listed as n/a. The next smallest group is also listed as "n/a" to prevent disclosing the group size smaller than five. We note that the "Black", "Latine" and "Southeast Asian" groups have all fewer than 20 respondents. We also note that the largest group after "White" (at 620) and "Unknown" (at 462) is "East Asian", at 78. In addition, we note that when combining all sources of missing information (not responding to the survey, skipping the question, or choosing prefer-not-to-answer), we have 64.8% of faculty members identifying with one or more racial identity groups.

Regarding the survey results for Canadian Indigenous identity, in this case, we had 409 individuals who did not provide an answer, 32 who chose "prefer-not-to-answer" to either Q5 or Q5.1. Thus, there are 441 individuals for whom Indigenous identity is unknown. A total of 865 individuals either answered "no" to Q5 or indicated they were not Indigenous from Canada in Q5.1. A total of five individuals responded that they were Indigenous from Canada. Table 5.2 below summarizes these results. Here we also remind the reader that our data set only included faculty members employed on May 1, 2020, and thus before the Black and Indigenous Excellence cluster hires.

There were 410 faculty members with a recorded sex-at-birth of female and 901 recorded as male. This information came from WorkDay.

Due to the substantial overlap of unknown racial identity and unknown Indigenous identity, we merged these unknown categories when cross-tabulations are discussed and in the regression analysis. Such merging protects individual confidentiality as well as limits issues of collinearity in our estimation. Thus, for the remainder of this report the Unknown group is defined as the set of faculty members for whom either their racial identity or their Indigenous identity is unknown. In other words, it is the union of the two Unknown groups reported in Tables 5.1 and 5.2, of respective size 462 and 441. This merged group is of size 468. We note that because Indigenous identity is not the same as racial identity, an individual may not have answered the question on racial identity but responded they were Indigenous from Canada, such that they are included both in the merged Unknown group and the Indigenous from Canada group.

5.2 Summary Statistics by Identity Group, Faculty and Rank

Table 5.3 presents summary statistics by identity group. This table is particularly important as a first step to identify which work-related characteristics may be behind potential salary gaps. To give an idea of the variation around the averages for each group, we provide the standard errors on each of them. First, we note that among the identity groups, those who selected "Another Race" (n=n/a) have been at UW the longest (17.7 years on average), followed by "Unknown" (n=468) and "White" (n=620). Faculty members who selected "South-East Asian" (n=9), "Black" (n=15) and "Indigenous from Canada" (n=5) have the lowest average years at UW. These latter groups also are among the most recent graduates, representing 11.7, 13, and 10.8 average years since highest degree respectively. As will be seen in the subsequent section, these differences account for a large part of the salary differences.

Looking at the average merit scores, which for each faculty member is the average of their available R scores from 2014 to 2020 inclusive, we note the averages by category vary from 1.57 (Indigenous from Canada) to 1.71 (Another Race).[14] We note that this total deviation is similar to the difference in merit scores across rank between Assistant and Full Professors, as shown in Table 5.6. We note that average merit scores differ across Faculties as well, with faculty members in Math exhibiting lower average R scores than faculty members in Arts, Engineering and Environment, as seen in Table 5.6. Insofar as racialized faculty may be disproportionately represented among some ranks and in particular Faculties, these differences are important to understanding differences in average merit. Additional information on this issue is discussed in Section 7 when we estimate what characteristics "explain" average R scores from 2014-2020, in an effort to investigate whether or not this variable is itself free of inequities, an issue raised by some members in the community, as mentioned in previous sections.

In terms of the average number of OPAs, first we note that to be eligible to receive this award, a faculty member needs to have a merit score in the top 20% of their academic unit. Thus, the number of faculty members who qualify is quite small. Here we observe from Table 5.3 that only the "Another Race" identity group has an average above 1. Recall that this is very small group. We also note that those who responded they were Indigenous from Canada are too small a group and collectively have too few OPAs to permit reporting. The very small size of this group also prevents us from disclosing much information on its composition across ranks, but as we see in Table 5.4, Canadian Indigenous faculty are more heavily distributed toward the ranks of assistant and associate professor. This distribution might go some way to explaining lower OPAs because these ranks correlate with lower R scores and lower frequency of OPAs compared to full professors. Indeed, we note in Table 5.7 that the distribution of OPAs by rank varies substantially, with Full Professors being the likeliest to have received at least one OPA.

As we further investigated OPAs (in Section 7) and sought to determine if they were given in a way that was potentially hiding biases, we discovered that the distribution of OPAs is notably influenced by Faculty, as shown in Table 5.8. Here as in Table 5.7, it is important to note that this data includes all OPAs received by all faculty members included in our data set, which as mentioned before is as of May 1, 2020. Hence when looking at the distribution of OPAs by Faculty as is done in Table 5.8, the pattern of departures due to retirements, resignations and other causes together with hiring patterns can be a reason

[14] Although not presented in this report, we also looked at faculty member's merit scores for each individual year and note that for some groups, the average R scores are consistently low, but for other groups (e.g. for those identifying Black), the R scores are often below, but sometimes above the reference group.

to explain the differences we see across Faculties, in particular when looking at the average number of OPAs by faculty member in each Faculty.

However, there is another reason that explains these differences across Faculties, which is the formula used to determine each Faculty's Selective Increase Pool, as per the MoA Section 13.3.2, which in turn determines the OPA allotment by Faculty, as detailed in the MoA Section 13.3.3(d). Since the formula depends on how salaries in each Faculty compare with the T1 and T2 threshold, Faculties with comparatively higher salaries have a relatively lower share of the OPA allotment. To verify this, in Table 5.9 we provide, based on the May 1, 2020 salaries and corresponding thresholds T1 and T2 in force at the time, the number of faculty members above T2, between T1 and T2, and below T1, described by the corresponding SIU contribution for each. On the last row we give the proportion of the Selective Increase Pool divided by the proportion of the Faculty size. If this number is, say 0.95, it means the Faculty's share of the Selective Increase Pool is 95% of the Faculty's share of UW when measured by faculty members. A number smaller than 1 implies there is correspondingly less OPAs to give out per faculty member in this Faculty than for Faculties with a number large than 1. This last row will prove useful to explain some of what transpires in Section 7 when we model OPAs.

Further to the concerns raised by faculty members around rank, we note that group-specific summary statistics by Rank and Academic Unit are not releasable due to small cell counts. Even providing distributions of race by Faculty and rank is difficult given some of the small groups in the data set. We can, however, provide some non-numeric comparative information. In Tables 5.4 and 5.5 we provide the rank and Faculty composition of faculty members for all UW and then indicate with a + or – whether a given group has a higher or lower representation in the given Faculty or rank than the overall group. For example, from Table 5.4 we observe that approximately 31% of faculty members at UW hold an Associate Professor rank. Table 5.4 then indicates that more than 31% of Indigenous faculty members hold an Associate Professor rank. It is important to note that a '+' simply indicates a proportion larger than the one shown on the last row, and as such it could be that the underlying proportion is only very slightly larger than for all of UW, or could be much larger. A similar caution holds for what a '-' means. Here we reiterate that we chose to provide information in this way to avoid disclosing small cell counts. At the same time, the non-numeric comparative information does prove to be useful when interpreting some of the results obtained in the next sections.

From Table 5.5 we note that Black-identifying respondents are more heavily represented in Arts, Science and Health, Middle Eastern respondents are more concentrated in Engineering, and East Asian-identifying respondents are more concentrated in Engineering, Mathematics and Science. Among the ranks, from Table 5.4 we see that Black, Middle Eastern, South East Asian, Mixed, and Female respondents are more likely to be concentrated in lecturer and assistant professor positions, while East Asian respondents are more likely to be in assistant professor positions.

5.3 Unknown Racial or Indigenous Identity

In this sub-section we consider the issue of unknown racial or Indigenous identity. Racial or Indigenous identity is unknown for two broad reasons: 1. an individual did not complete the survey (or skipped that specific question), or 2. an individual chose "prefer not to answer". Again, we combine these two groups into a single "unknown" category for missing information, and then consider both those who have an unknown racial or unknown Indigenous identity.

The concern for our analysis is whether this identity information is missing randomly or non-randomly. That is, those individuals for whom we don't know what their answer to the question of interest is cannot be assumed to be distributed similarly to the rest of the sample (in terms of the different variables of interest in our salary model). At the same time, we cannot assume that the faculty members who did not provide an answer would all have identified with the largest group for the given question (e.g., “white” for racial identity).

When information is missing for a very small fraction of the observations, and in an apparent random manner, observations with missing information are typically dropped. However, in this data set, there is a substantial number of observations with missing data, and the attributes of this group appear to be non-random, as we describe next.

Table 5.10 breaks down the unknowns by rank and sex.[15] We see that there is a marked difference in unknowns by sex across all ranks, with the overall unknown rate for female faculty members being 21.7% while it is 42.1% for male faculty members. Notably, the largest unknown rate for female faculty members is at the assistant professor level (28.7%) but is lower than the smallest unknown rate for male faculty members which is for the lecturer group, at 30.9%. By rank, the largest unknown rate is observed for full professors at 39.9% while the smallest is for lecturers at 24.9%.

The disparity in the unknown rate with respect to these two variables reinforces our belief that we should not assume that those who did not answer the survey (or chose prefer-not-to answer) are otherwise similarly distributed as the overall faculty population. Thus, our data may suffer from non-response bias. We perform sensitivity analysis around our primary model to consider whether our estimated coefficients are sensitive to this potential bias. This sensitivity analysis is presented in Appendix A.3.

6. Regression Analysis

Table 6 presents estimated results from the model presented in Section 4.1. The coefficients on the racial and Indigenous identity variables represent the identity-based salary gaps after controlling for work-related characteristics. We discuss these results, and the caveats and concerns regarding the analysis and the data below.

We observe that while most racial and Indigenous Identity Groups have small to modest positive coefficients, the coefficient estimate for Black is -3920, for Latine is -2189, and for Mixed is -3747. Further, the coefficient estimate for Indigenous from Canada is -4235. As indicated in the previous paragraph, these coefficients represent the average salary differences between these groups and the reference group after controlling for all the work-related variables included in the model. For example, this means Black faculty members’ salaries are on average lower than the reference group for racial identity by $3,920 after controlling for work-related characteristics.

We pause here to highlight some caveats and cautions regarding the analysis and the data. First, we draw attention to the large standard errors on the coefficient estimates for identity groups. As mentioned before, these coefficients represent the average salary gaps that remain after controlling for work-related characteristics. The large standard errors tell us that while the <u>average gap</u> is -$3,920 for Black faculty members, there is a lot of variability. Some Black faculty members might have salaries much lower than what the model would predict based on their work-related characteristics (contributing to making the corresponding coefficient for this identity group being negative), while others may have a higher actual salary than what the model predicts. In other words, if we were to provide a histogram of these individual

[15] We also considered a break down looking at just non-response rates. The resulting table is substantively similar; however, we cannot report more fine-grained breakdowns of responses due to small cell sizes, in order to protect the identities of our faculty members.

differences between actual and predicted salaries for this identity group, it would be centered on a negative value but would have a relatively large spread rather than a narrow peak.

Second, many categories have a very small number of respondents from which we are estimating these gaps. Moreover, because of the small number of respondents in some groups, we expect that the estimated gaps may vary considerably in future iterations of these analysis. Similar year-by-year variation is evinced (and noted) in the annual Berkeley Salary Equity Reports (Basri et al., 2015). This variation is to be expected because with small groups the addition (or loss) of one or two faculty members could have a large impact on the average. For example, there are only 15 faculty members who have identified as Black in our data set. Appendix A.5. contains an analysis which explains the potential implications of small samples with illustrative examples.

Third, information on racial and Indigenous identity is missing for a large proportion (approximately 35%) of our faculty members. We do not know if the missing information is correlated with identity groups, but the fact that individuals for whom we don't have an answer on racial or Indigenous identity do not seem distributed similarly to the rest of the population (as shown in Table 5.10) suggests that the model's coefficient estimates could be biased (up or down) by this non-random missing information. Also, and in relation to the previous point: because the group size is so small, if the racial and Indigenous identity of only a few of the individuals with missing information became known and was associated to some of the smaller groups, this could potentially have a large impact on the value of the estimated coefficients for these groups. See Appendix A.5. for an illustrative example.

Fourth, as already noted in Section 5, the averages of work-related characteristics varied across these racial and Indigenous identity groups. While these variations explain differences in salaries, as mentioned earlier, the most prevalent concern raised by faculty members is that if there are biases in the allocation of Merit scores, OPAs, and Rank (factors determined at UW, henceforth referred to as "upstream factors"), this could lead to hidden inequities in our salary model. For this reason, in Section 7 we investigate further if these three variables themselves have unexplained gaps by racial identity or Indigenous identity.

Finally, here we note that our primary model is an additive model. That is, for individuals who responded "yes" to more than one racial identity category, the model implies an assumption that each such category additively contributes to their estimated salary. This is a strong assumption. Ideally, we would test it by including interaction terms in the regression model between the categories that have common respondents and if the corresponding coefficients for these interaction terms were near 0, we would then have more confidence in this assumption. But we are not able to perform this type of verification because there are too few faculty members in these intersections.

7. Upstream Factors Analysis

In this section we take a closer look at rank, merit scores and OPAs.[16] This analysis is not meant to suggest that these variables should not be used in the salary model, since at least in the case of merit and OPAs, there is a very direct contribution to the salary given our salary structure. This analysis is rather meant to explore if these factors are themselves free of unexplained gaps or biases. If they are not, then future quantitative and qualitative investigations and studies could be used to better understand the

[16] We note that these factors "explain" a substantial portion of the salaries for faculty members.

process by which such gaps may be created and how they could in turn be corrected. Exploring models that either include all controls relevant to the outcome (salary, in our case) or include only those that have very little potential for being “tainted” by bias or other forms of inequities, is a common approach when analyzing wage gaps. This section is in line with this dual approach.

For the analysis in this section, we removed one influential data point that was exerting an extreme influence on some of the models explored in this section.

7.1 Regression model with fewer factors

First, we consider a regression model similar to our primary model but where merit and OPA are excluded, and current Rank is only considered as a binary (lecturer vs non-lecturer). Results are shown in Table 7.1.

There we see that the coefficient for Mixed became very negative compared to what it was in the primary regression model. Coefficient estimates for Black and Latine are also more negative than in the primary regression model. Similarly, the coefficient for Indigenous from Canada became more negative (around -9,766 instead of -4,235 in our primary regression model) and with a p-value modestly above 0.1. This dramatically different coefficient estimate is likely related to the number of OPAs for that group. Finally, we note that the Unknown group now has a coefficient of about -1900. While this is worth noting, by definition we have no information on this group other than its members did not provide an answer for either racial or Indigenous identity. Later in this section we see that an unexplained gap is observed for this group for both merit scores and OPAs, which is consistent with what we observe in Table 7.1 from the model that doesn’t include these explanatory variables.

7.2 A closer look at rank

Next, we consider rank. Here a potential concern is that progress through the ranks, for tenure/tenure-track faculty members, could be affected by their racial/Indigenous identity, or sex/gender. There are several limitations in our data that prevent us from performing a thorough examination of this concern, namely because the only information we have is rank-at-hire, and current rank. We do not have information about when an individual faculty member changed rank. Also, since progress from assistant to associate professor is closely determined by Policy 77 in terms of timing, what may be illuminating is to focus on the rank of (full) professor, and test whether a logistic regression model is able to explain whether or not someone has reached this rank, using the work-related characteristics Years at UW, Years at UW Squared, Rank at Hire, and Faculty (to account for potential differences in practices across Faculties). We then examine whether or not gaps are detected when we introduce equity variables. We exclude from this analysis members who were hired as professors.

In Table 7.2 we see that when we include the equity variables in Model 2 (middle column), Black, Middle Eastern, East Asian, and South Asian have positive coefficients, while Latine and Another Race have negative coefficient estimates. [17] The high standard errors indicate that there is substantial variation in outcomes, and given the very small numbers in these groups, that is not surprising. Model 3 (third column) is almost the same as Model 2 except we remove the rank-at-hire variable, which does not affect the coefficients of the equity variables much.

7.3 A closer look at merit scores

[17] There is no coefficient estimate for Indigenous from Canada because none have full professor rank and also for Mixed, as there is no faculty member in this group who transitioned to the full professor rank after being hired..

Next we turn to merit scores. In this case we use Current Rank and Faculty as explanatory variables, as there are clear differences by rank and also by Faculty. In particular, we see that Math and (to some extent) Science have negative coefficients, as seen in Table 7.3 (first column). We note here that from the point of view of merit increases, it is not an issue that some Faculties tend to give higher merit scores than others, as each Faculty receives a pool of funds (roughly) based on its size, and then merit increases are allocated from that pool, independently from merit scores in other Faculties.

It is useful to point out that the model does not explain much of the variation in merit scores, with an adjusted R-squared of less than 0.2 (i.e., the explanatory variables used in this model are only able to account for less than 20% of the variability in the merit scores). This is somewhat reassuring, in that as discussed before, these scores are (as they should be) determined by a variety of factors and information that are not in this data set. So we are expecting to see a large amount of variability after controlling for things like rank and Faculty.

Once we include the equity variables in Model M2 (middle column), we note that East Asian and Unknown have negative coefficients with little variation from that mean effect (low standard errors). This is consistent with what we observed when we replace Current Rank with a binary, and remove Merit and OPAs from the primary model (as seen in Table 7.1), which causes the coefficients for these two categories to become negative while they were both positive in the primary regression model. Negative coefficients but high standard errors are observed for all identity groups except Southeast Asian, Another Race Category, and Female, which have positive coefficients. Interestingly, we see that when we remove Current Rank and add Years at UW and Years at UW squared (see Model M3 in third column), the model coefficients do not change much.

7.4 A closer look at OPAs

Finally, we examine OPAs. Since this variable can only take integer values (0,1,2,3…) we propose to use logistic regression to model the binary response “OPA recipient”, which is 0 if the faculty member never received an OPA and 1 otherwise. Given that by design OPAs depend on merit, it seems necessary to include Merit as one of the explanatory variables, along with Current Rank (as per Table 5.8). However, rather than including the average merit score as done so far in all models, we created a binary variable called "TopR" that is 1 if the faculty member’s average merit score is over the 70th percentile of average merit scores in their Faculty, and 0 otherwise,

Our model also includes Years at UW, Years at UW squared and Faculty, for reasons discussed in Section 5.2. The summary for this model is shown in the leftmost column of Table 7.4, under “Model 1”. Note that Engineering, Arts, Math and Science have negative coefficients, and in the case of Engineering and Math the standard errors are small. When we include the equity variables (second column, labeled “Model 2”)[18], the one category that has a small standard error relative to its coefficient is the Unknown category, which has a negative coefficient, indicating these faculty members are less likely to have received an OPA. Other groups have negative coefficients but larger standard errors. We then investigated another model (third column, labeled “Model 3”) where the TopR merit indicator and Current Rank are removed from the model. Doing so causes the coefficient on Middle Eastern to become negative, but does not change the sign of any of the other coefficients for the equity variables when we introduce them in the model (4th column, Model 4), although now East Asian and Unknown (negative) and Another Race (positive) have small standard errors relative to their coefficient estimates.

We note that for both models (1) and (3), when we include the equity variables, the coefficients for Engineering and Math become less negative and have larger standard errors. This suggests that some of

[18] There is no estimated coefficient for Mixed because there are no OPAs for this group.

these inter-Faculty differences are potentially getting picked up by the equity variable coefficients, since Engineering, Math and Science also happen to be the Faculties where there is a higher concentration of faculty members from the East Asian, South Asian and Unknown groups (as seen in Table 5.5), which are three groups that have negative coefficients in Models (2) and/or (4), and which (for East Asian and Unknown) have small standard errors. Of course, this could also go in the reverse direction (the Faculty variables are picking up part of the racial group differences). While it may be hard to tell which affects which, Tables 5.8 and 5.9 at least provide information on the fact that by design, OPAs are given in a way that is not independent from which Faculty a member is in because of the formula used to determine the Selective Increase Pool.

8. Discussion and Interpretation of Results

The gaps estimated by the regression coefficients in Table 6 can be viewed as the salary differences that remain for the corresponding groups compared to the reference group after controlling for the work-related characteristics that are chosen as explanatory variables in this salary model. In other words, these are the gaps that the model is unable to explain using these work-related variables, based on the specific form in which they are used in the model. The analysis cannot provide an explanation for why these gaps remain. Moreover, the multiple issues with the data used to perform this analysis (notably the large proportion of missing data and the fact that many identity-based groups are quite small, with fewer than 20 respondents) also complicates inferences drawn from the estimated coefficients. We note that the removal or addition of just a few observations, or the mischaracterization of just a few individuals, can have dramatic implications for coefficient estimates in the case of small groups. We provide examples to illustrate.

The examples depicted in Appendix A.5 suggest that we may anticipate large differences in the small-group coefficient estimates over time, as slight changes in the composition of these small groups can have a large impact on the estimated (average) salary gaps.

Finally, we note that as a by-product of this review, the results of Sections 7.3 and 7.4 have highlighted differences between Faculties that could be useful within university-wide committees when comparing merit scores and the prevalence of OPAs across campus.

9. Recommendations

9.1 Recommendations regarding potential adjustments

Because of the complexities highlighted throughout this report, the SAWG members have differing opinions as to which course of action is most appropriate: making salary adjustments versus not making salary adjustments, based on the estimation results. In particular, we do not have consensus on what constitutes reasonable criteria for identification of systemic gaps in this context. We elaborate below providing both historical and analytical considerations.

First, we note that the question of what constitutes “identification” of systemic gaps is controversial, even with less complicated data. Many scholars would say we cannot claim to have truly identified systemic gaps in this analysis due to the issues raised in our report. However, it should be clear that many of the same scholars would also say the same for the 2015 analysis because, despite the better data of 2015, the analysis is still subject to selection bias and lack of adequate controls for productivity characteristics. The question then becomes, what criteria are sufficient for the University to consider that an underlying systemic gap may exist and to make group-based adjustments?

In 2015, the first time the regression approach was used for group-based gap analysis at UW, the criteria for adjustment were not set in advance. This makes sense as an initial approach when the SAWG is uncertain as to the complexities of the study. The results of the 2015 analysis were such that it was deemed reasonable to make an adjustment (after controlling for work-related characteristics, female faculty earned on average $2,905 less than male faculty, and both the p-value and the standard error on the estimate were small). Given the 2015 analysis, the SAWG who did the analysis in 2020-2021 was in a better position to come up with decision criteria beforehand, which they formulated in terms of a low p-value and a large gap size relative to the median UW faculty salary.

The task to "identify any race-based anomalies" as stated in the 2021-2024 MoSS, and to develop the appropriate decision criteria, may have been assumed to be relatively easy, given the gender-based anomaly/gap analysis done in 2015-16 and 2020-2021. However, Indigenous and race-based analysis is far more complex, as explained throughout this report. Also, the nature of the data used for this analysis differs in significant ways from the data used in the gender-based analysis from 2015-16 and 2020-21.[19]

In addition to the data-related issues already raised in the report, there are further complications arising for an Indigenous/race-based analysis and decision criteria. For one, there are few members of Indigenous groups and racialized groups. With small group sizes, there is a smaller likelihood of low p-values. Therefore, setting low p-values as a criterion for making adjustments could be seen as a systematic barrier to correcting race-based gaps.

We must also consider that race is not binary. There are multiple identified racialized groups, which raises the question of what the comparison group should be. In the current time frame, 'white' is the dominant majority group in the university context, and has a social location associated with socio-economic, cultural, and political advantages. However, the SAWG is cognizant of the fact that white may not be the reference group used in the future. While we acknowledge that the precedent set in this current analysis does not need to be followed in future analyses, we are also aware that it may set expectations. Therefore, we should be clear in our understanding of both short and long-term implications of the present decisions. We also note that the next review is quickly approaching in 2025.

The determination of the base group is intertwined with another issue, and that is: whether adjustments are only made when the estimated coefficient is negative, i.e., adjusting only the groups that are making less than the reference group. The 2020-2021 group had not ruled out a correction in either direction, i.e., no choice was made beforehand as to which group (male or female faculty members) would be eligible for a correction and which group wouldn't. In the context of a race-based analysis, in which there are multiple groups and a need to define a single reference group (baseline), this decision becomes vastly more difficult. For example, we note a very large positive coefficient on "SouthEast Asian," which is a very small group of faculty members. Would this estimate then imply that the white majority should get a pay raise to account for the higher average salary of this small group? Or are adjustments to be restricted to minority groups only?

The choice of reference group does not matter too much for the purpose of estimating gaps other than providing a baseline. But it has important implications if group-based adjustments are to be made only for

[19] The gender data used for these previous analyses was based on the sex-at-birth data collected by HR, typically at the time of onboarding.

groups with negative gaps relative to the reference group. If done this way, in the long run, positive gaps for some groups would remain under this approach, thereby potentially causing the reference group to essentially have a systemic negative gap. Or corrections could be made to the reference group as well. In that case, there is a *possibility* of flip-flopping of salary adjustments in the long run. Although we wouldn't expect flip-flopping, the *possibility* of it raises the question of if and how this issue should be addressed.

It is also important for the institution to think about what would happen if the largest group were to change as a result of shifting demographics at UW, e.g., would "white" no longer be the reference group?

We also wish to point out that "resolving" any identity-related salary gaps comes with the additional complication that, depending on how it is done, there could be discrepancies between the groups on which the analysis is based, and those who receive salary corrections. E.g., if individuals leave UW or if responses can be changed post-analysis, then those receiving adjustments may differ from those on which the gaps were estimated. This complication is especially likely given the time lag between when such a correction would take place (2024) and the timestamp of the data (May 1, 2020), which is a lag of at least four years. We understand that, in the current context UW cannot retroactively address this concern, but we raise it for future adjustment decisions, where there will be some lag, but not as much as the current situation.

It is also important to note that when it comes to race, Indigeneity, sex-at-birth and gender[20], it is not just how faculty members identify but also how people perceive them that is part of how discrimination might generate systemic gaps. Data based on self-declaration captures the former but not necessarily the latter. This complicates the assessment as to whether a group-based gap is due to discriminatory actions arising from perceptions of racial identity, versus salary gaps derived from factors external to UW (e.g. due to historical and/or market factors).

We realize that the SAWG's lack of consensus, on whether or not an adjustment should be made based on the estimates presented, places an additional decision-making burden on the Provost and FAUW President. To mitigate this, below we are providing additional guidance and address the systemic gap identification questions as directly as we can.

1. Has the working group identified systemic gaps?

Identification of a systemic gap requires agreement upon criteria as to whether a systemic gap has been identified.

What we can say is that with the available data, and after controlling for work-related characteristics, estimated results show Indigenous faculty have average salaries lower than non-Indigenous salaries (by $4235), and that Black, Latine and Mixed racial groups have average salaries that are lower than white salaries (by $3920, $2189, and $3747, respectively). The standard errors and p-values are such that this estimated gap would not pass the p-value criterion established by the 2020-2021 gender analysis. However, there is a concern that this criterion should not be applied in the race-based analysis because it has a high likelihood of failing given the small group sizes, and therefore the decision criterion could itself reflect systemic bias.

[20] Here we refer to the gender identity question in the equity survey.

2. What criteria are appropriate for identification of race and Indigenous based salary gaps, and for the recommendation of salary adjustments?

The current SAWG, like previous ones, agrees that a size criterion is necessary to make salary adjustments. The current SAWG agrees with the cutoff chosen by the 2020-2021 SAWG at 1% of the median salary, which was approximately $1,500 in 2020.

We are, however, not unanimous on any additional criterion, e.g., use of standard error or p-value cutoffs, or other criteria.

For example, small group sizes, missing information on race and Indigeneity, in addition to the paucity of controls for productivity measures, make the group concerned that the model is under or over-estimating the gap. In addition, high standard errors indicate a large degree of variation.

However, the group is not unanimous as to how and whether these should be used as criteria for making salary adjustments. On one hand, these issues have implications on the accuracy of the estimated gaps. On the other hand, none of these issues are expected to change in the next several decades, and therefore, using them as criteria at best puts up a systemic barrier based on methods best suited for larger data (e.g., by requiring a small p-value criterion) and, at worst, (e.g., by requiring a smaller non-response rate) gives undue influence to one set of employees over another

A cautious approach is needed when formulating criteria to determine if there is a race-based anomaly/gap or not. This is true not just for the current situation but also due to the long-term repercussions that themselves create or maintain group-based gaps. Moreover, there are further complexities with respect to how the analysis is conducted in terms of granularity. For example, if a minimum group size is required to conclude a gap was identified, but at the same time members of racialized groups prefer to be defined in a more granular way, this could cause many groups to never meet the requirements to be considered for a group-based correction.

Given these complexities, the group is not unanimous on the best course of action and has purposefully not made any statement about application of these estimates and whether an adjustment should or should not be made.

The SAWG recognizes the difficulties of making these decisions and has provided a table (below) to help weigh the technical pros and cons of making an adjustment now based on the estimated gaps from the primary regression analysis.

Supporting a Salary Adjustment Now	Opposing a Salary Adjustment Now
*After controlling for work-related characteristics, the average salaries of Black, Latine, Mixed, and Indigenous faculty members is shown to be several thousand less than white faculty members. This is the difference in salaries, on average, calculated using the population of faculty at UW with the information they provided.	*The standard errors on the estimated race coefficients are quite high and there are many issues with the data (missing information, small group size, etc.), such that we cannot conclude that our estimate is an accurate measure of systemic inequity. We may be over- or underestimating any systemic inequity, to the extent that even the sign of some of these estimates may be incorrect.
*While we can improve the analysis with better data, we are unlikely to have complete data or sufficient group sizes to obtain precise estimates any time soon. (Aggregation of racial categories/groupings might help, but given that statistical agencies are moving away from aggregation & using more granular categories, the relevant UW stakeholders are likely to be similarly opposed to aggregation). We should have a very clearly defined set of criteria which have a reasonable probability of being met if the plan is to wait until the next round.	*We could wait until the next round, or the one after, when we might have better data and the benefit of previous work to determine prior to the analysis what would be considered sufficient evidence of a significant (systemic) gap such that it requires an adjustment. With better data (and perhaps different groupings) we can improve our ability to estimate systemic gaps.
*Given the expectation that small group sizes will continue to be the case in the population of faculty at UW, and given that "prefer not to answer" continues to be in the choice set, any decision rule based on statistical significance is problematic. Because statistical significance is unlikely in this case, such a decision rule may be viewed as equivalent to a pre-set decision to not make changes.	*The 2015 and 2020 analysis used statistical significance measures (p-values) to identify whether they were confident in the estimated salary inequities. Similar measures could be applied here.
*This SAWG was not unanimous on the appropriate decision rule and decided a priori to simply present the findings. This decision provides some flexibility in available actions.	*Deciding which groups get corrected post-analysis could appear arbitrary in the absence of previously agreed upon thresholds, and inconsistent with the approach taken for the previous 2020-2021 gender-based analyses, which could in turn appear to be inequitable.

*With only a small number of faculty members in these groups, it is not very costly. It may be preferred to potentially "over-correct" than to make no correction at all.	*Any correction made may over-correct or under-correct relative to an underlying "true" salary inequity, especially if the set of individuals receiving it is inconsistent with the groups used to estimate the gaps. Taking no action may be perceived as better than taking an action that is potentially incorrect.
*Corrections may be made on faculty employed at the time (2020), with the exception of those who have left UW.	*Corrections may be problematic especially if the set of individuals receiving it is inconsistent with the groups used to estimate the gaps. And if corrections are limited to those employed at UW in 2020, newer hires may be upset at not receiving these corrections (as occurred with the gender corrections). The 4-year gap between now and the time-stamp of the data and analysis would exacerbate this issue.
*Doing the correction now may simply correct the problem, and would not necessarily result in repeated corrections. It may simply remove the need for future corrections.	*If we keep correcting groups every time they have a negative gap but (of course) never correct positive gaps, is there not a chance we will converge toward an equilibrium where all groups are making more than the reference group and if that's the case, are we ok to engineer such a salary model?

9.2 Recommendations for Future Work

Based on discussions and concerns arising during this analysis, the Salary Anomaly Working Group notes that while our current analysis faced a number of conceptual and methodological challenges, this work has helped to illuminate several avenues that could assist in improving UW's ability to identify and address identity-based gaps. They are summarized below in no particular order.

- **Further Evaluation and Monitoring of Internal Assessment Processes and other Inputs to Salary (Upstream factors), including Merit Scores, OPAs, Rank and Starting Salaries** – As noted in this report, as well as in the consultations, we are cautious in both our interpretation of the coefficient on identity coefficients (that these are gaps we cannot explain), as well as in our use of internal assessment factors as controls (that by including these controls we run "the risk of explaining discrimination with discrimination"). Thus, the Salary Anomaly Working Group recommends further monitoring of these productivity measures, and inputs to the salary process, such as Merit, OPAs, Rank, which could prevent the introduction of biases by identity group via these channels. We also recommend further monitoring and analysis of starting salaries (data permitting), which we reiterate are not included as a control in the primary regression model. Qualitative analysis could be useful in these contexts particularly given the small group sizes.

- **Continued improvement in data collection (use of Workday data) and consultation** – Consultations with both equity groups and end users of the equity data will be important practices to maintain and enhance at UW to ensure that the data is appropriate and supportive of the analyses, as well as ensuring respondents are fully informed of the data's intended uses. In particular, the question of how to define individuals eligible for a group-based salary correction (e.g., will UW use the self-reported identity at the time of data collection or at a later time) will need to be addressed. Moreover, given concerns over response rates and data validation, the SAWG recommends that equity data collection continues via the formal HR-employee platform (currently Workday), rather than using Survey data.

- **Analysis of Additional Groups** – During consultations the Salary Anomaly Working Group noted interest in including additional equity groups in the analysis (e.g. disability, gender identification). Based on these discussions, and on the identity questions deemed important in the 2021 Equity Survey, and on the text in the Memorandum of Salary Settlement to "*investigate all cases",* the next Salary Anomaly Working group may wish to consider inclusion of additional identity groups in the analysis. We add a caveat here that with some identity categories, the number of observations may be even smaller than those of the race-based identity categories, and thereby run into the same small sample issues discussed in the current analysis. Therefore, additional qualitative analysis could be useful in this case, similar to race.

- **Collection and Application of Data Across Time** – Particularly in the context of disability, but also in the context of other equity identities, the question of timing was raised. For example, the impact of a disability on salary is likely to depend on the timing (onset) and duration of the disability. Collection of changes in identity markers over time could help to better identify whether group-based biases exist when timing may have important implications on salary. Additional intertemporal data, such as time in rank, leaves and temporary reduced workload, are also important in the investigation of potential biases (not because of the direct impact on salaries – we use full time equivalent salaries, but because of the potential effect this has on the long run salary impact. These have been used and proposed as important factors for gender and ethnicity wage gap studies). This data could also help UW assess the impact our current leave policies and whether the impact differs across equity groups. Finally, tracking exits from UW (faculty members who leave UW for various reasons) would be important to assess potential sample selection which may bias our estimates of salary gaps. Tracking exits (and reasons for exits) would also help UW assess both retention success, as well as equity practices on a broader scale.

- **Tracking Chronic Anomalies** – Further to concerns of the potential sources of bias, the SAWG recommends that UW track across time and analyze whether individual anomalies identified by the Anomalies process, exhibit common characteristics. For example, among the anomalies identified in any given year or across time, is there a large proportion belonging to any specific groups?

- **Exploration of interactions** – Subject to sufficient sample size, exploration of interactions could enrich our understanding of the impact of performance scores on salary. For example, OPAs and merit scores are Faculty-dependent.

- **Review by relevant stakeholders of the identity groups used for salary analysis** – prior to the next cyclical salary anomaly review, it would be useful to have a discussion among stakeholders to weigh the pros and cons of using the more granular racial identity groups originating from the equity census categories which avoid the problem of aggregation bias, versus creating larger groups that may be more amenable to the type of statistical analysis required for the review by avoiding the small sample issue that the current analysis has faced.

Appendices

A1. Equity Survey Questionnaire

See next page.

UNIVERSITY OF WATERLOO EQUITY SURVEY

INTRODUCTION

The University of Waterloo is confidentially collecting equity data about its students and employees. The purpose of this survey is to understand the makeup of our community in order to identify equity gaps in our programs, services, and policies. Your responses are critical to help us to do this work.

This survey asks respondents to describe themselves by selecting the terms that best match their identity along several dimensions, including the following: disability, racial identity, Indigenous identity, gender identity, sexual identity, religious and spiritual affiliation, family education background, and Canadian residency status.

Please share as much information as you are comfortable disclosing, so we can have the most accurate and complete understanding of our students and employees.

NOTES ABOUT THIS SURVEY

- The survey takes approximately 5 – 10 minutes and will be available until October 31, 2021.
- Participation in the survey is confidential and voluntary. You can skip any question you are not comfortable answering by leaving it blank or by choosing the "I prefer not to answer" option.
- The survey does not ask for any personally identifying information and your answers will never be attributed to you as an individual. Reports will include only summarized results so that no individual can be identified.
- If you require assistance or alternative means to participate in the survey, wish to no longer receive reminders about this survey or wish to withdraw any responses you have provided, please email equitysurvey@uwaterloo.ca.
- By participating in the survey, you are agreeing that you are aware your participation is voluntary, and you are free to withdraw from the survey at any time.
- For more information about the survey, we encourage you to visit the Equity Survey webpage and read the Frequently Asked Questions (FAQs).

Please return this completed survey by email to equitysurvey@uwaterloo.ca

DISABILITY

1. Are you a person with one or more disabilities?

Definition: For the purposes of this survey, disability is a physical, mental, intellectual, emotional, developmental, cognitive, learning, communication, or sensory impairment – or a functional limitation or difference. A disability could be permanent, temporary, or episodic in nature. It could be readily evident or invisible. The disability may result in a person experiencing a disadvantage or encountering barriers to full participation in university life.

Select only ONE (1) option

◯ Yes

◯ No (Go to question 2)

◯ I prefer not to answer

1.1. If *Yes*, please select the box(es) below that apply to you.

Please note that these options are not meant to be comprehensive. There are many forms of disability that may not be listed here, and disability experience is very diverse and always changing.

Select ALL that apply

☐ Neurodivergent (e.g., Autism spectrum, Attention Deficit Disorder, Attention Deficit and Hyperactive Disorder, dyslexia, dysgraphia, Tourette's, etc.)

☐ Autoimmune disorder (e.g., lupus, fibromyalgia, rheumatoid arthritis, HIV/AIDS)

☐ Blind or visual impairment (e.g., unable to see or difficulty seeing, retinopathy, glaucoma, cataracts, etc.)

☐ Cognitive or learning disability (e.g., traumatic brain injury, stroke, concussion; difficulties using symbols or spoken language)

☐ Upper extremity limitations (e.g., coordination, dexterity, difficulty using hands or arms, for example, grasping or handling paper towels or using a point-of-sale machine)

☐ Deaf or hard of hearing (e.g., tinnitus, sensorineural, conductive hearing loss, acoustic neuroma, age-related hearing loss)

☐ Mental health (e.g., depression generalized anxiety disorder, bipolar disorder, obsessive compulsive disorder, personality disorders, or additions)

☐ Mobility (e.g., difficulty moving around, for example, from one office to another or up and down stairs, maintain prolonged sitting or standing, use of mobility device such as cane, crutches, wheelchairs, scooters)

☐ Nervous system condition (e.g., migraine headaches, Parkinson's disease, Multiple sclerosis/MS)

☐ Ongoing Medical condition (e.g., epilepsy, diabetes, Crohn's, cancer)

☐ Speech impairment (unable to speak or difficulty speaking and being understood, e.g., aphasia, apraxia, dysarthria, dysphonia)

☐ Another disability (please specify): ____________________

☐ I prefer not to answer

GENDER

2. Please select the gender identity option(s) with which you identify.

Select ALL that apply

- ☐ Woman (includes cis women, trans women, and everyone else who identifies as a woman)
- ☐ Man (includes cis men, trans men, and anyone else who identifies as a man)
- ☐ Gender non-conforming
- ☐ Non-binary
- ☐ Agender
- ☐ Questioning
- ☐ Trans
- ☐ Two-Spirit
- ☐ Another gender identity (please specify): ____
- ☐ I prefer not to answer

3. Please indicate the pronouns you use.

Select ALL that apply

- ☐ She/Her/Her(s)
- ☐ He/Him/His
- ☐ They/Them/Their(s)
- ☐ Xe/Xem/Xyr(s)
- ☐ Ze/Hir/Hir(s)
- ☐ Hir/Hir/Hir(s)
- ☐ Another pronoun (please specify): ____
- ☐ I prefer not to answer

SEXUAL IDENTITY

4. Please select the sexual identity option(s)with which you identify.

Select ALL that apply

- ☐ Asexual
- ☐ Bisexual
- ☐ Gay
- ☐ Heterosexual/straight
- ☐ Lesbian
- ☐ Pansexual
- ☐ Queer
- ☐ Questioning
- ☐ Another sexual identity (please specify): ____
- ☐ I prefer not to answer

INDIGENOUS IDENTITY

5. Do you identify as an Indigenous person?

Select only ONE (1) option

- ◯ Yes
- ◯ No (Go to question 6)
- ◯ I prefer not to answer

5.1. If Yes, please specify with which Indigenous nation/culture you identify.

Select ALL that apply

- ☐ An indigenous person from Canada (i.e., First Nations [status or non-status], Métis, or Inuit/Inuk)
- ☐ An Indigenous person from outside Canada (for example Saami, Maori, Ainu, Aymara...) (please specify: ______
- ☐ I prefer not to answer

5.1) If an Indigenous person from Canada, do you identify as:

Please select ALL that apply

- ☐ First Nations, status or non-status (please specify the name of the First Nation or Indian Band): ______
- ☐ Métis
- ☐ Inuit/Inuk
- ☐ I prefer not to answer

5.2. If Métis, are you a registered member of a Métis organization or settlement?

Please select ALL that apply

- ☐ No
- ☐ Yes, the Métis Nation of Ontario
- ☐ Yes, the Manitoba Métis Federation
- ☐ Yes, the Métis Nation Saskatchewan
- ☐ Yes, the Métis Nation of Alberta
- ☐ Yes, the Métis Nation British Columbia
- ☐ Yes, another Métis Organization or Settlement (please specify): ______
- ☐ I prefer not to answer

5.3. If Inuit/Inuk, are you enrolled under, or a beneficiary of, an Inuit land claims agreement?

Please select ALL that apply

- ☐ No
- ☐ Yes, Inuvialuit Final Agreement
- ☐ Yes, Nunavut Agreement (Nunavut Land Claims Agreement)
- ☐ Yes, James Bay and Northern Québec Agreement (Nunavik)
- ☐ Yes, Labrador Inuit Land Claims Agreement (Nunatsiavut)
- ☐ Yes, another land claims agreement (please specify): ______
- ☐ I prefer not to answer

RACIAL IDENTITY

Our society often describes people based on their race or racial background (e.g., "White" or "Black"), though these categories are complex, often overlapping, and not necessarily aligned with region or nationality.

6. Please select the racial category or categories with which you primarily identify.

Select ALL that apply

- ☐ Black e.g., African, Caribbean, Black Canadian, Afro-Latine, African American, or other African descent
- ☐ East Asian e.g., Chinese, Korean, Japanese, or other East Asian descent
- ☐ Latine e.g., Latin American, Hispanic descent
- ☐ Middle Eastern e.g., Afghan, Egyptian, Iranian, Lebanese, Turkish, Kurdish, or other Arab or Persian descent
- ☐ South Asian e.g., East Indian, Pakistani, Bangladeshi, Sri Lankan, Indo-Caribbean, or other South Asian descent
- ☐ Southeast Asian e.g., Filipino, Vietnamese, Cambodian, Thai, Malaysian, Indonesian, or other Southeast Asian descent
- ☐ White e.g., British, German, Ukrainian, or other European descent
- ☐ Another race category (please specify): ____________________
- ☐ I prefer not to answer

RELIGION AND SPIRITUAL AFFILIATION

7. Please indicate your religion and/or spiritual affiliation.

Select ALL that apply

- ☐ No religious affiliation
- ☐ Bahá'í faith
- ☐ Buddhism
- ☐ Christianity
- ☐ Hinduism
- ☐ Indigenous spirituality
- ☐ Islam
- ☐ Jainism
- ☐ Judaism
- ☐ Sikhism
- ☐ Another religion or spiritual affiliation (please specify): ____________________
- ☐ I prefer not to answer

EDUCATION

8. What is the highest level of education you have achieved to date?

Select only ONE (1) option

- ◯ Did not finish high school
- ◯ Graduated from high school
- ◯ Some or completed college or CEGEP
- ◯ Some university (first degree in progess)
- ◯ Completed a bachelor's degree (BA, BSc, etc.)
- ◯ Completed a master's degree (MA, MSc, etc.)
- ◯ Completed a doctoral degree or professional degree (PhD, JD, MD, etc.)
- ◯ Other (please specify): ____________________
- ◯ I prefer not to answer

9. *[If Q8 highest education ≠ Did not finish or graduated from high school]* **Are you part of the first generation in your immediate family to attend university?**

Select only ONE (1) option

- ◯ Yes
- ◯ No
- ◯ Not sure
- ◯ I prefer not to answer

CANADIAN RESIDENCY

10. What is your residency status in Canada?

Select only ONE (1) option

- ◯ Canadian Citizen
- ◯ Work/study permit holder
- ◯ Permanent Resident
- ◯ Refugee or Refugee claimant
- ◯ Visitor visa holder
- ◯ I prefer not to answer

11. How long have you lived in Canada?

Select only ONE (1) option

- ◯ I was born in Canada
- ◯ Less than 1 year
- ◯ 1 year to less than 3 years
- ◯ 3 years to less than 5 years
- ◯ 5 years or longer
- ◯ I prefer not to answer

CONCLUSION

Thank you for participating in the University of Waterloo Equity Survey.

Your responses will help us understand the makeup of our community and support the development of strategic initiatives, programs, and supports to meet the needs of under-represented and equity-deserving members of our entire community.

As this is an ongoing collection process, you will have the opportunity to update your survey responses when survey reminders are issued (at least once a year). If you no longer wish to receive messages about this survey or wish to withdraw your submitted responses entirely or resubmit your response, please contact equitysurvey@uwaterloo.ca.

Please note that if you choose to withdraw your survey responses, no historical data you submitted will be used to generate further reports or analysis (previous reports cannot be changed).

If you would like to be included in further communications on institutional equity data, provide feedback or comments on the survey, or would like more information about the survey and how results will be used, please visit the University of Waterloo Equity Survey webpage.

A2. Variables used in regression model

We first list the variables that are not equity-related.

- Years at UW
- Years at UW squared
- Merit (average merit score out of 2.0 for available years, denoted as R.mean in the table below)
- Number of previous Outstanding Performance Awards (OPA)
- Lag of years between highest degree and Year of hire
- Highest degree (factor, comparison is Bachelor)
- Current Rank (factor, comparison group is Assistant Professor)
- Academic Group (factor, comparison group is Health)
- Rank at Hire (factor, comparison is Assistant Professor)
- Interaction between Academic Group and binary variable for Lecturer vs Professorial Rank
- Interaction between Lag and Rank at hire

The equity variables were introduced in the model by defining 11 binary variables as follows:

- Each of Black, East Asian, Latine, Middle Eastern, South Asian, South East Asian, Another Race, and Mixed were set to be "TRUE" for a given faculty member if they chose any of those racial identities when responding Question 6 in the Equity Survey. (Mixed was not a category available to select in the equity survey, but was a category generated by IAP based on the write in responses that used this exact term.)

- The variable "Indigenous from Canada" was set to be TRUE for those who answered positively to the corresponding Question 5.1 in the Equity Survey.

- The variable "Unknown" was set to be TRUE if either (i) the faculty member skipped the racial or Indigenous identity questions, chose "prefer-not-to-answer" for either the racial identity or Indigenous identity question (general or from Canada), or did not complete the survey.

- The variable "Female" was set to be TRUE for faculty members who are recorded as "female" in the sex-at-birth data field on WorkDay, and is defined as assigned sex-at-birth.

A.3 Sensitivity Analysis for Missing Data

Analysis of salary inequities by race and Indigeneity is substantially more complex than the 2020 analysis on sex assigned at birth due to a number of factors, including issues arising from the quantity of Identity Groups, and from missing information. While several aspects of our results could be studied further via various sensitivity analyses, here we chose to focus on Missing Data.

We also considered doing sensitivity analysis to study disability and its interaction with race and Indigeneity, but the number of observations in these intersectional groups becomes so small that not all could be estimated (because there is no one in that category), and those who may still suffer from having one observation that is highly influential and results in extreme coefficient estimates.

Regarding missing data, we reported in Section 5.3 that unknown racial identity is not random. In Table A.1, we consider whether our coefficient estimates are stable if we run the model on a sample where all observations with unknown racial and or Indigenous identity are dropped. We do see small differences, but the coefficient estimates remain relatively similar.

We might also note that we considered a log-level model, where Salary is logged, and that the results are substantively similar, (noting that coefficient estimates from log-level models must be transformed if one wants a dollar value for the gap).

A.4. Salary Increases

Algebraically, a faculty member's salary growth can be characterized by equation (1).

$$\text{salary}_{t+1} = \text{salary}_t * (1 + \text{scale}_{t+1}) + \text{Radj}_t * \frac{\text{FSIP}}{\sum_{\text{fac}} \text{Radj}} + \text{Any Individual Adjustment} \qquad \text{(eq.1)}$$

where,

$$\text{Radj} = \begin{cases} \text{R if salary} < \text{T1} \\ \max(0, \text{R-0.75}) \text{ if salary between T1\&T2} \\ \max(0, \text{R-1.25}) \text{ if salary} > \text{T2} \end{cases}$$

salary_t = base salary at a given time, t.
R = the average merit score a faculty member receives on their annual performance feedback.
T1 = Threshold 1 (T1 differs for tenure/teaching stream, but is otherwise constant across rank)
T2 = Threshold 2 (T2 differs for tenure/teachings stream, but is otherwise constant across rank)
FSIP = Faculty Selective Increase Pool (the amount is Faculty specific)
and
'Any Individual Adjustment' refers to OPAs, Anomalies and any other discretionary adjustments.

Each year, a faculty member's base salary increases by a fixed scale rate (same for everyone), plus a share of a faculty "pie" (FSIP)[21] (the size of the share depends on their relative merit score), plus (in some cases) a flat increase due to an OPA, or an anomaly or other discretionary adjustment. Administrative and other stipends are not included in equation 1 because they are not permanent and do not impact base salaries. Note that starting salaries would be represented in equation (1) as the very first base salary: salary_0, where t=0 represents a faculty's first year at UW. (See online technical appendix for further details and illustrative examples)

[21] FSIP is determined by the Selective Increase Unit (SIU) and by where faculty members' salaries are relative to T1 & T2. Each year the SIU, T1, T2 and floors are increased by scale, so that merit increases keep pace with the scale increase.

A.5. Sensitivity Analysis around Small Sample Issues

The estimated results from Section 6 are a calculation of the average salary gaps remaining after controlling for salary related characteristics. In this appendix, we provide the reader with a few cases that illustrate how, with small samples (particularly those with wide variation), just a few changes can lead to widely different estimates. We stress that this analysis is not statistically rigorous in that we make arbitrary decisions about which scenarios to explore and then only use 10 random repetitions to illustrate the variability of the coefficients. Our goal here is simply to provide the reader with a more intuitive explanation of the impact of this variability, as measured by the standard error on the regression coefficients, on the interpretation of the model.

The first case we consider is motivated by our recent cluster hires. What would happen if we hire 10 new faculty members who identified as Black?

We add ten new observations randomly selected (without replacement) by duplicating from among the existing observations (note: racial identity is then adjusted to be Black). We then re-estimate the model, and find that the coefficient estimate on Black is smaller in magnitude than observed in our main report. We repeat the exercise 10 times, and find that in most cases, the estimated gap is smaller. Sometimes the gap is much smaller, sometimes it is only slightly smaller, and in one case it is larger. See Figure A.1, which provides a visualization of the estimated coefficients, with the vertical line indicating the coefficient estimated in the main regression model reported in Section 6 (Table 6). We consider alternative scenarios, where the new observations are drawn from lower (blue) vs higher (green) salaries. This case also allows us to explore the concerns raised that cluster hires may exhibit very different salary distributions than those hired before the cluster program.

The second case we consider, addresses another concern: what if we were to or have lost Black faculty members, how might that have impacted the estimated gap?

We randomly select two faculty members who identify as Black, remove these from the data, then re-estimate the model. Again, we find that the coefficient estimate changes. We repeat the exercise and find that the estimated gap is sometimes larger and sometimes smaller in magnitude. We also find that if we restrict the random selection to be those earning above the mean, the gap tends to be larger; and if we restrict to those earning below the mean, the gap tends to be smaller, as we might expect. See Figure A.2. However, we also note that even if the selection is among those earning below the mean, the estimated gap can increase.[22]

We then consider the scenario that there was an error in the identity group selected by the faculty member. We look at this case from two angles: one, that a faculty member may have accidentally selected into one of the unknown categories; and two, that a faculty member may have accidentally selected Black. See Figures A.3-A.4. As with the previous case, changing just two observations can make a large difference in the estimated gap for Black faculty members (ranging from the two to five thousands in this limited example).

[22] The estimated gap can increase because the random draws are from below the mean salary (not below the mean residual). Some individuals with lower salaries may also have very low work-promoting characteristics, such that after controlling for these, the residual is negative (and the gap is larger).

We repeat (many of) these exercises for the Indigenous from Canada group, which is a much smaller group – containing only five faculty members. As might be expected, the resulting variation in coefficient estimates is substantially larger, as seen in Figure A.5. Adding ten randomly selected Indigenous faculty members results in widely different coefficient estimates each time. If the additions are randomly selected from amongst those with salaries larger than the average salary for faculty members who identified as Indigenous from Canada, the salary gap often becomes positive. And if randomly selected from amongst those with salaries lower than the average for Indigenous from Canada, the salary gap sometimes gets larger (more negative). In Figure A.6, we explore a similar scenario as in Figure A.3, where we randomly switch two from Unknown to Indigenous from Canada. There again we see very wide variations in the value of the corresponding coefficients.

As a final illustration, we explore what happens when we take five faculty members who identified as Unknown and switch them to identifying as the base group (White). As shown in Table A.2, we find that this switch has very little impact on the racial coefficient estimates, as expected given the very large number of faculty members in both the Unknown and the White group.

References

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Tables for Report on Salary Anomalies by Race and Indigenous Identity
Prepared by 2023-2024 Salary Anomaly Working Group

September 1, 2024

Table 5.1: Count by racial identity answers: n/a indicates a group size too small to disclose

East.Asian	Black	Latine	MiddleEast	SouthAsian	Southeast.Asian	White	Mixed	Another	Unknown	sum
78	15	19	53	51	9	620	n/a	n/a	462	1317

Table 5.2: Count by Canadian Indigenous identity answers

No	Unknown	Yes	sum
865	441	5	1311

Table 5.3: Average values of quantitative factors by group along with standard errors; an 'n/a' indicates a number that is too sensitive to release; Mixed is omitted because its size is too small to release any information on those quantitative factors

group	Yrs UW	std err	Yrs Highest Deg	std err	R	std err	Nb OPAs	std err	Count
East.Asian	10.8	1	15.7	1	1.56	0.02	0.59	0.12	78
Black	8.7	1.7	13	1.8	1.61	0.04	0.53	0.27	15
Latine	10.3	2	13.7	2.1	1.59	0.04	0.53	0.21	19
MiddleEast	10.3	1.1	15.2	1.3	1.63	0.03	0.79	0.18	53
SouthAsian	12	1.3	18.8	1.4	1.63	0.03	0.88	0.2	51
Southeast.Asian	6.9	1.5	11.7	2.4	1.68	0.06	0.44	0.18	9
White	12.7	0.4	18.4	0.4	1.65	0.01	0.94	0.05	620
Another	17.7	5.9	21.3	5.3	1.71	0.07	2.17	0.7	n/a
Unknown	13.9	0.5	19.4	0.5	1.59	0.01	0.78	0.06	468
IndigCan-No	12.2	0.3	17.8	0.3	1.63	0.01	0.89	0.04	865
IndigCan-Yes	9.2	2.4	10.8	1.9	1.57	0.04	n/a	n/a	5
Female	10.7	0.4	16.1	0.5	1.63	0.01	0.78	0.06	410
Male	13.7	0.3	19.3	0.3	1.62	0.01	0.88	0.04	901
UW	12.8	0.3	18.3	0.3	1.62	0.01	0.85	0.03	1311

Table 5.4: Breakdown by rank of different groups compared to all of UW: a '+' indicates that the proportion of respondents for the group shown on that row whose rank is listed in that column is higher than the proportion of UW faculty members in that rank, given on the last row of the table. A '-' indicates that proportion is smaller than the UW proportion.

	Assistant Professor	Associate Professor	Lecturer	Professor	count
IndigCan	+	+	-	-	5
Unknown	+	+	-	+	468
East.Asian	+	-	-	-	78
Black	+	-	+	-	15
Latine	+	+	+	-	19
MiddleEast	+	-	+	-	53
SouthAsian	+	-	-	+	51
Southeast.Asian	+	-	+	-	9
Mixed	+	-	+	-	n/a
Another	+	+	-	-	n/a
Female	+	-	+	-	410
UW	0.16	0.31	0.18	0.35	1311

Table 5.5: Breakdown of groups by Faculty compared to all of UW: a '+' indicates that the proportion of respondents for the group shown on that row whose Faculty is listed in that column is higher than the percentage of UW faculty members belonging to that Faculty, given on the last row of the table. A '-' indicates that proportion is smaller than the UW proportion.

	HLTH	ARTS	ENG	ENV	MATH	SCI	count
IndigCan	+	+	-	+	-	-	5
Unknown	-	-	+	-	+	+	468
East.Asian	-	-	+	-	+	+	78
Black	+	+	-	-	-	+	15
Latine	+	+	+	-	+	-	19
MiddleEast	-	-	+	-	-	-	53
SouthAsian	+	-	+	-	+	-	51
Southeast.Asian	+	+	+	+	-	-	9
Mixed	-	+	-	+	-	+	n/a
Another	+	+	-	+	-	-	n/a
Female	+	+	-	+	-	+	410
UW	0.06	0.24	0.25	0.07	0.21	0.16	1311

Table 5.6: Average values of R score by rank and Faculty

Rank	HLTH	ARTS	ENG	ENV	MATH	SCI	Rank Average
Assistant Professor	1.52	1.56	1.52	1.59	1.39	1.51	1.51
Associate Professor	1.58	1.63	1.6	1.62	1.47	1.55	1.58
Lecturer	1.67	1.65	1.68	1.63	1.57	1.62	1.63
Professor	1.7	1.76	1.73	1.73	1.64	1.64	1.7
Faculty Average	1.61	1.65	1.65	1.65	1.55	1.59	1.62

Table 5.7: Distribution of the number of OPAs by rank: shown are the proportions of faculty members from each rank who have received the number of OPAs shown on the leftmost column

	Assistant Professor	Associate Professor	Lecturer	Professor
0	0.86	0.62	0.70	0.32
1	0.13	0.25	0.22	0.19
2	0.01	0.10	0.05	0.20
3	0.00	0.04	0.03	0.15
4	0.00	0.00	0.01	0.10
5	0.00	0.00	0.00	0.04
6	0.00	0.00	0.00	0.00

Table 5.8: Distribution of the number of OPAs by Faculty: shown are the proportions of faculty members from each Faculty who have received the number of OPAs shown on the leftmost column

	HLTH	ARTS	ENG	ENV	MATH	SCI
0	0.57	0.56	0.58	0.49	0.61	0.54
1	0.23	0.21	0.18	0.31	0.18	0.20
2	0.10	0.12	0.11	0.11	0.10	0.12
>=3	0.09	0.11	0.12	0.08	0.11	0.14
Avd. Nb OPA per individual	0.78	0.85	0.87	0.83	0.80	0.91

Table 5.9: Distribution of SIU values and Selective Increase Pool Relative to Size by Faculty: shown on the first three rows are the proportions of faculty members in each Faculty whose SIU value (defined in MoA 13.3.2) is given by the value shown in the leftmost column: the last row shows the ratio of the Faculty's relative size measured in SIU values over the Faculty's relative size measured in number of faculty members

	HLTH	ARTS	ENG	ENV	MATH	SCI	UW
0.25	0.02	0.04	0.08	0.03	0.11	0.09	0.07
0.5	0.25	0.28	0.46	0.23	0.33	0.36	0.35
1	0.73	0.68	0.45	0.74	0.56	0.55	0.58
Selective Increase Pool relative to Faculty size	1.11	1.07	0.91	1.12	0.97	0.97	1

Table 5.10: Distribution of Missing Information (‘Unknown’ response for either race or Indigeneity) by rank and gender (sex assigned at birth)

	Tot Nb Female	Tot Nb Male	% Unknown Fem	% Unknown Male	% Unknown
Assistant Professor	87	127	28.7%	42.5%	36.9%
Associate Professor	124	279	16.9%	45.2%	36.5%
Lecturer	94	139	16.0%	30.9%	24.9%
Professor	105	356	26.7%	43.8%	39.9%
total	410	901	21.7%	42.1%	35.7%

Table 6: 2020 Model + Equity Identity Groups

	2020 Model		
	Coefficient Estimate	Standard Error	p-value
Indigenous from Canada	-4235	5153	0.411
Black	-3920	3033	0.196
East Asian	716	1402	0.610
Latine	-2189	2657	0.410
Middle Eastern	134	1676	0.936
South Asian	108	1676	0.948
South East Asian	2197	3862	0.570
Another race category	-788	4750	0.868
Mixed	-3747	5807	0.519
Unknown	-34	742	0.963
Female	-299	729	0.682
Rest of ARTS	-10185	3898	0.009
Cheriton School of Computer Science	2645	4393	0.547
ENG	10880	3839	0.005
ENV	-4107	5331	0.441
Economics	6222	5798	0.283
Rest of Math	-1130	3867	0.770
School of Pharmacy	27824	6715	0.000
School of Accounting and Finance	6757	4512	0.135
Rest of SCI	-4575	4184	0.274
School of Optometry and Vision Science (SOVS)	16962	7746	0.029
Graduate License	-8129	7509	0.279
Professional	16532	4643	0.000
Master's and Equivalent	9406	3730	0.012
Doctoral	9630	3707	0.009
Years @ UW	3018	133	0.000
Years @ UW squared	-29	3	0.000
Average Rs 2014-20	24822	2176	0.000
Number of OPAs	3953	382	0.000
Lecturer or Clinical Lecturer	-10987	4115	0.008
Associate Professor	7424	1250	0.000
Professor	14722	1583	0.000
Lecturer or Clinical Lecturer at Hire	-3219	1945	0.098
Associate Professor at Hire	2522	2413	0.296
Professor at Hire	26683	3855	0.000
Lag Between Degree and Hire	985	146	0.000
TenureTrack x ARTS	3796	4231	0.370
Tenure Track x CS	19978	4775	0.000
Tenure Track x ENG	3442	4128	0.405
Tenure Track x ENV	-1806	5644	0.749
Tenure Track x ECON	7960	6321	0.208
Tenure Track x MATH	12806	4216	0.002
Tenure Track x PHARM	-8168	7305	0.264
Tenure Track x SAF	35888	5078	0.000
Tenure Track x SCI	3774	4510	0.403
Tenure Track x OPT	-3220	8007	0.688
Lag x Associate Professor at Hire	844	264	0.001
Lag x Lecturer or Clinical Lecturer at Hire	-134	177	0.448
Lag x Full Professor at Hire	392	233	0.093
Constant	61246	5273	0.000
Observations	1311		
rmse	11300.8		
F	284.9		
df_m	49		
df_r	1261		
r2_a	0.914		

Table 7.1: Upstream 2020 Model with Lecturer vs Non-Lecturer instead of full current rank categories and without OPA and merit

	Coefficient Estimate	Standard Error	P-value
Indigenous from Canada	-9766	6729	0.147
Black	-5979	3959	0.131
East Asian	-1677	1824	0.358
Latine	-4034	3469	0.245
Middle Eastern	420	2186	0.848
South Asian	330	2186	0.880
South East Asian	692	5038	0.891
Another race category	3981	6184	0.520
Mixed	-10016	8619	0.245
Unknown	-1919	962	0.046
Female	-535	953	0.575
Controls from 2020 model excluding OPA & Merit, and replacing binary lecturer/non-lecturer control instead of current rank	Yes		
Observations	1310		
rmse	14769.1		
F	169.9		
df_m	45		
df_r	1264		
r2_a	0.853		

Table 7.2: Full Professor Logit Models

	Model 1	Model 2	Model 3
	coef/se/p	coef/se/p	coef/se/p
Black		0.64 (0.99) [.52]	0.56 (0.88) [.52]
East Asian		0.48 (0.39) [.22]	0.74 (0.37) [.045]
Latine		-0.37 (0.79) [.64]	-0.32 (0.77) [.68]
Middle Eastern		0.88 (0.49) [.073]	0.81 (0.45) [.074]
South Asian		0.97 (0.52) [.061]	1.06 (0.47) [.024]
Another race category		-0.95 (1.25) [.45]	-0.39 (1.34) [.77]
Unknown		0.14 (0.21) [.51]	0.16 (0.19) [.39]
Female		-0.03 (0.21) [.89]	-0.22 (0.20) [.27]
Years @ UW	0.46 (0.04) [0]	0.47 (0.04) [0]	0.45 (0.04) [0]
Years @ UW squared	-0.01 (0.00) [4.1e-13]	-0.01 (0.00) [2.7e-13]	-0.01 (0.00) [1.1e-15]
Lecturer or Clinical Lecturer at Hire	-2.38 (0.36) [3.0e-11]	-2.34 (0.36) [8.6e-11]	
Associate Professor at Hire	1.52 (0.26) [4.0e-09]	1.54 (0.26) [3.9e-09]	
ARTS	-0.86 (0.42) [.041]	-0.90 (0.42) [.033]	-0.95 (0.40) [.019]
SCI	-0.39 (0.44) [.37]	-0.47 (0.44) [.28]	-0.51 (0.42) [.22]
ENG	-0.07 (0.41) [.87]	-0.24 (0.42) [.57]	-0.28 (0.40) [.48]
ENV	-0.07 (0.50) [.89]	-0.10 (0.50) [.84]	0.12 (0.48) [.8]
MATH	-0.12 (0.43) [.78]	-0.21 (0.43) [.63]	-0.47 (0.41) [.25]
Constant	-5.62 (0.54) [0]	-5.79 (0.56) [0]	-5.39 (0.51) [0]
Observations	1221	1221	1221
ll	-398.0	-394.0	-449.6
chi2	703.6	711.7	600.4
p	1.18e-145	2.90e-140	2.95e-118
r2_p	0.469	0.475	0.400

Coefficient Estimates presented with Standard Errors in parentheses (rounded) and P-values in square brackets underneath

Table 7.3: Merit Regressions

	Model 1	Model 2	Model 3
	coef/se/p	coef/se/p	coef/se/p
Indigenous from Canada		-0.02	-0.08
		(0.08)	(0.09)
		[.79]	[.33]
Black		-0.02	-0.03
		(0.05)	(0.05)
		[.68]	[.62]
East Asian		-0.06	-0.07
		(0.02)	(0.02)
		[.0038]	[.0021]
Latine		-0.04	-0.05
		(0.04)	(0.04)
		[.39]	[.28]
Middle Eastern		-0.03	-0.02
		(0.03)	(0.03)
		[.28]	[.39]
South Asian		-0.02	-0.01
		(0.03)	(0.03)
		[.51]	[.77]
South East Asian		0.06	0.04
		(0.06)	(0.06)
		[.33]	[.53]
Another race category		0.06	0.07
		(0.07)	(0.08)
		[.4]	[.37]
Mixed		-0.20	-0.23
		(0.10)	(0.11)
		[.053]	[.037]
Unknown		-0.05	-0.05
		(0.01)	(0.01)
		[.000032]	[.000054]
Female		0.01	0.00
		(0.01)	(0.01)
		[.44]	[.81]
Lecturer or Clinical Lecturer	0.13	0.12	
	(0.02)	(0.02)	
	[7.7e-14]	[9.5e-12]	
Associate Professor	0.07	0.06	
	(0.02)	(0.02)	
	[.000013]	[.000044]	
Professor	0.20	0.20	
	(0.02)	(0.02)	
	[2.6e-37]	[1.1e-35]	
ARTS	0.04	0.04	0.03
	(0.02)	(0.02)	(0.02)
	[.099]	[.072]	[.15]
SCI	-0.04	-0.03	-0.02
	(0.02)	(0.02)	(0.03)
	[.098]	[.22]	[.4]
ENG	0.02	0.03	0.04
	(0.02)	(0.02)	(0.02)
	[.46]	[.15]	[.11]
ENV	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)
	[.23]	[.22]	[.25]
MATH	-0.09	-0.08	-0.06
	(0.02)	(0.02)	(0.02)
	[.000098]	[.0012]	[.0092]
Years @ UW			0.01
			(0.00)
			[1.0e-11]
Years @ UW squared			-0.00
			(0.00)
			[1.8e-08]
Constant	1.52	1.53	1.56
	(0.02)	(0.02)	(0.02)
	[0]	[0]	[0]
Observations	1310	1310	1310
rmse	0.181	0.180	0.190
F	35.06	16.53	8.471
df_m	8	19	18
df_r	1301	1290	1291
r2_a	0.172	0.184	0.0932

Coefficient Estimates presented with Standard Errors in parentheses (rounded) and P-values in square brackets underneath

Table 7.4: model for indicator of OPA recipient

	Model 1 coef/se/p	Model 2 coef/se/p	Model 3 coef/se/p	Model 4 coef/se/p
Indigenous from Canada		-0.481		-1.280
		(1.151)		(1.158)
		[0.676]		[0.269]
Black		-0.168		-0.351
		(0.687)		(0.613)
		[0.808]		[0.568]
East Asian		-0.539		-0.598
		(0.336)		(0.283)
		[0.110]		[0.035]
Latine		-0.432		-0.665
		(0.652)		(0.566)
		[0.509]		[0.240]
Middle Eastern		0.019		-0.215
		(0.399)		(0.334)
		[0.962]		[0.519]
South Asian		-0.727		-0.441
		(0.443)		(0.334)
		[0.102]		[0.187]
Southeast Asian		0.424		0.457
		(0.886)		(0.719)
		[0.633]		[0.525]
Another Race		1.958		2.249
		(1.629)		(1.356)
		[0.230]		[0.098]
Unknown		-0.549		-0.543
		(0.170)		(0.143)
		[0.002]		[0.0002]
Female		0.254		0.076
		(0.171)		(0.143)
		[0.138]		[0.593]
Years at UW	0.212	0.209	0.240	0.241
	(0.030)	(0.030)	(0.021)	(0.022)
	[0.000]	[0.000]	[0.000]	[0.000]
Years at UW squared	-0.004	-0.004	-0.004	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)
	[0.00000]	[0.00000]	[0.000]	[0.000]
ARTS	-0.183	-0.147	-0.221	-0.196
	(0.327)	(0.333)	(0.274)	(0.278)
	[0.577]	[0.658]	[0.421]	[0.481]
ENG	-0.652	-0.442	-0.590	-0.419
	(0.330)	(0.343)	(0.276)	(0.285)
	[0.049]	[0.198]	[0.033]	[0.142]
ENV	0.350	0.406	0.254	0.283
	(0.399)	(0.405)	(0.333)	(0.338)
	[0.380]	[0.316]	[0.446]	[0.403]
MATH	-0.662	-0.445	-0.573	-0.430
	(0.342)	(0.352)	(0.283)	(0.290)
	[0.053]	[0.206]	[0.043]	[0.139]
SCI	-0.245	-0.084	-0.329	-0.207
	(0.343)	(0.351)	(0.291)	(0.295)
	[0.476]	[0.812]	[0.257]	[0.483]
TopR	2.970	2.986		
	(0.198)	(0.201)		
	[0.000]	[0.000]		
Associate Professor	-0.114	-0.071		
	(0.293)	(0.296)		
	[0.697]	[0.811]		
Lecturer	-0.548	-0.640		
	(0.316)	(0.321)		
	[0.083]	[0.047]		
Professor	0.227	0.311		
	(0.320)	(0.324)		
	[0.479]	[0.338]		
Constant	-2.519	-2.506	-1.955	-1.846
	(0.363)	(0.394)	(0.279)	(0.299)
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	1,310	1,310	1,310	1,310
Log Likelihood	-581.496	-571.640	-769.754	-757.409
Akaike Inf. Crit.	1,186.991	1,187.281	1,555.507	1,550.818

Note: Mixed is omitted because no OPA was received in this group

Table A.1: Sensitivity Analysis, drop missing

	(1) 2020 Model coef/se/p	(2) Drop Missing coef/se/p
Indigenous from Canada	-4235.00	-3353.49
	(5153)	(5936)
	[.411]	[.572]
Black	-3919.93	-3167.13
	(3033)	(3240)
	[.196]	[.329]
East Asian	715.96	577.02
	(1402)	(1467)
	[.61]	[.694]
Latine	-2188.55	-1580.79
	(2657)	(2798)
	[.41]	[.572]
Middle Eastern	134.18	-97.29
	(1676)	(1755)
	[.936]	[.956]
South Asian	108.44	-127.04
	(1676)	(1734)
	[.948]	[.942]
South East Asian	2197.30	3088.91
	(3862)	(3993)
	[.57]	[.439]
Another race category	-788.44	463.00
	(4750)	(5366)
	[.868]	[.931]
Mixed	-3747.22	-19.22
	(5807)	(6811)
	[.519]	[.998]
Unknown	-34.31	
	(742)	
	[.963]	
Female	-298.50	-288.00
	(729)	(887)
	[.682]	[.745]
Observations	1311	843
rmse	11300.8	11571.1
F	284.9	184.7
df_m	49	48
df_r	1261	794
r2_a	0.914	0.913

Coefficient Estimates presented with Standard Errors in parentheses (rounded) and P-values in square brackets underneath

Figure A.1: Add 10 Black

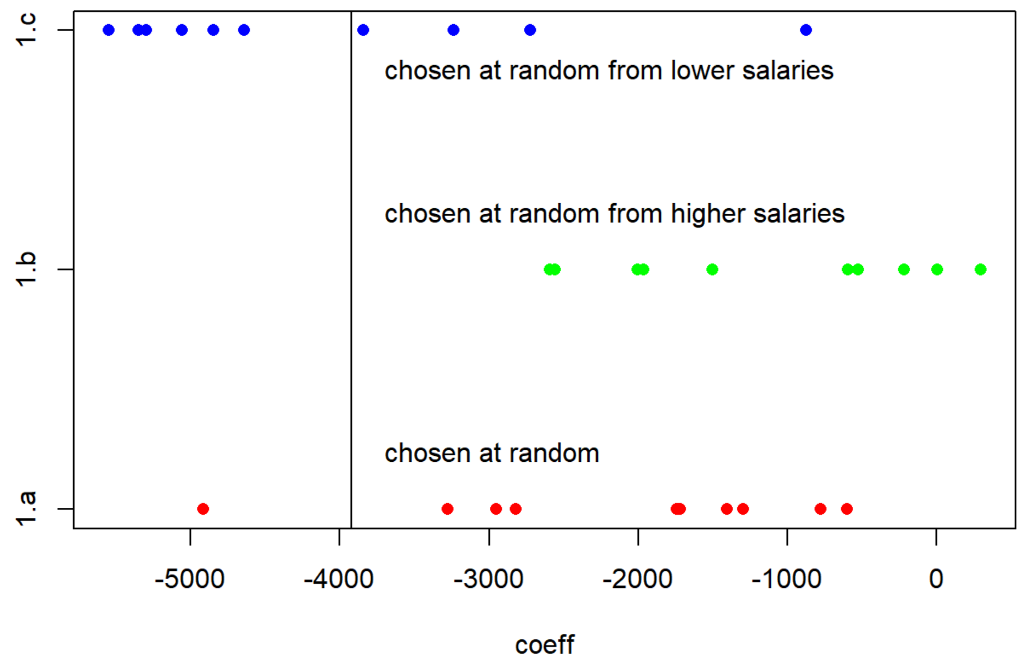

Figure A.2: Remove 2 Black

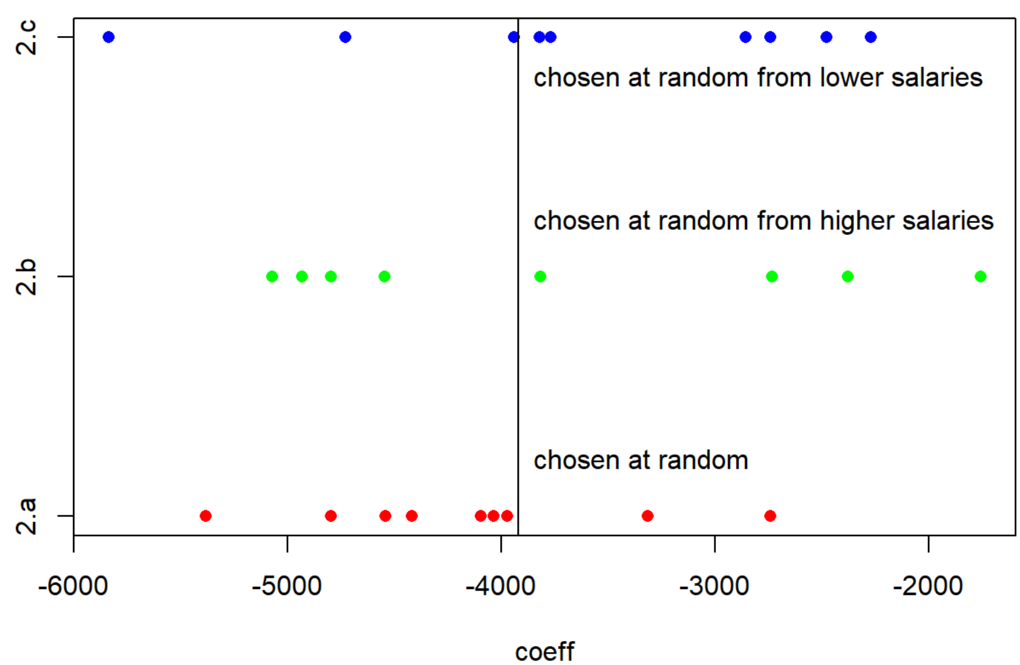

Figure A.3: Switch 2 from Unknown to Black

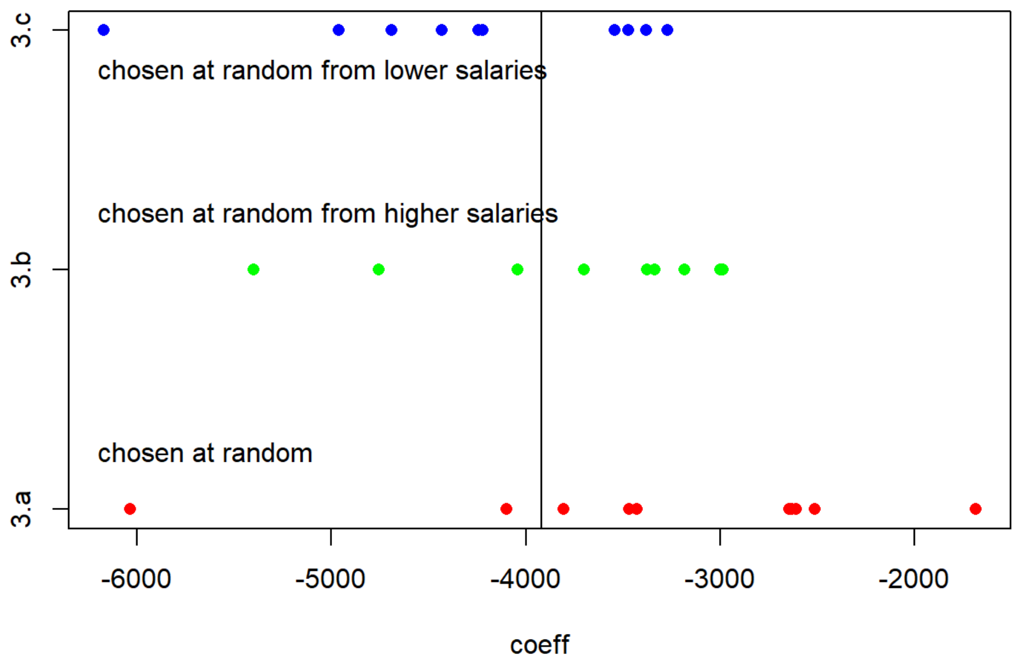

Figure A.4: Switch 2 from Black to Unknown

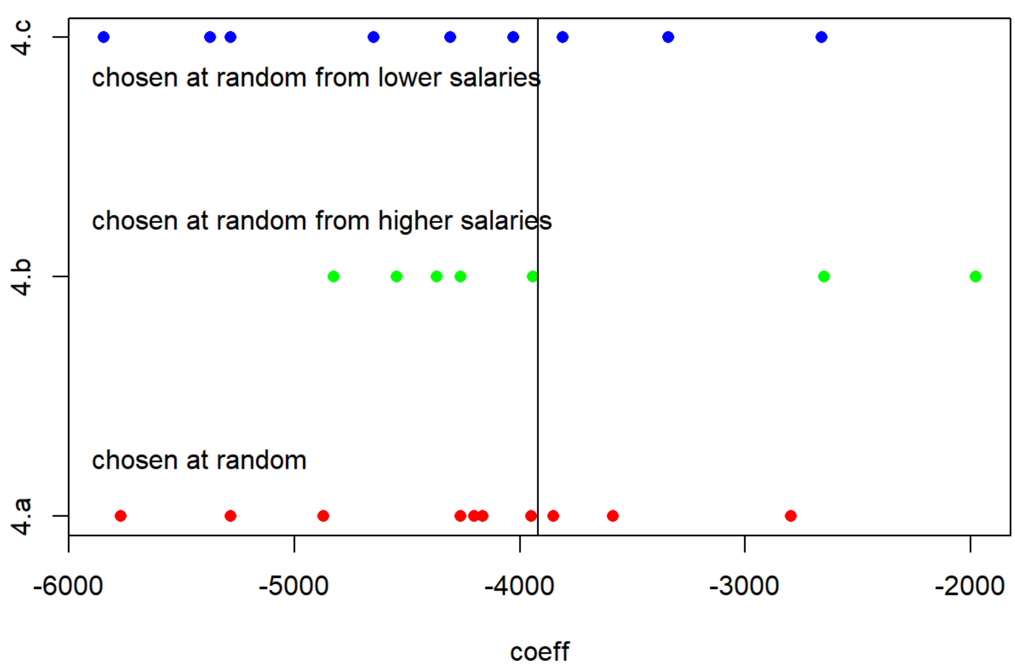

Figure A.5: Add 10 to Indigenous from Canada

Figure A.6: Switch two from Unknown to Indigenous from Canada

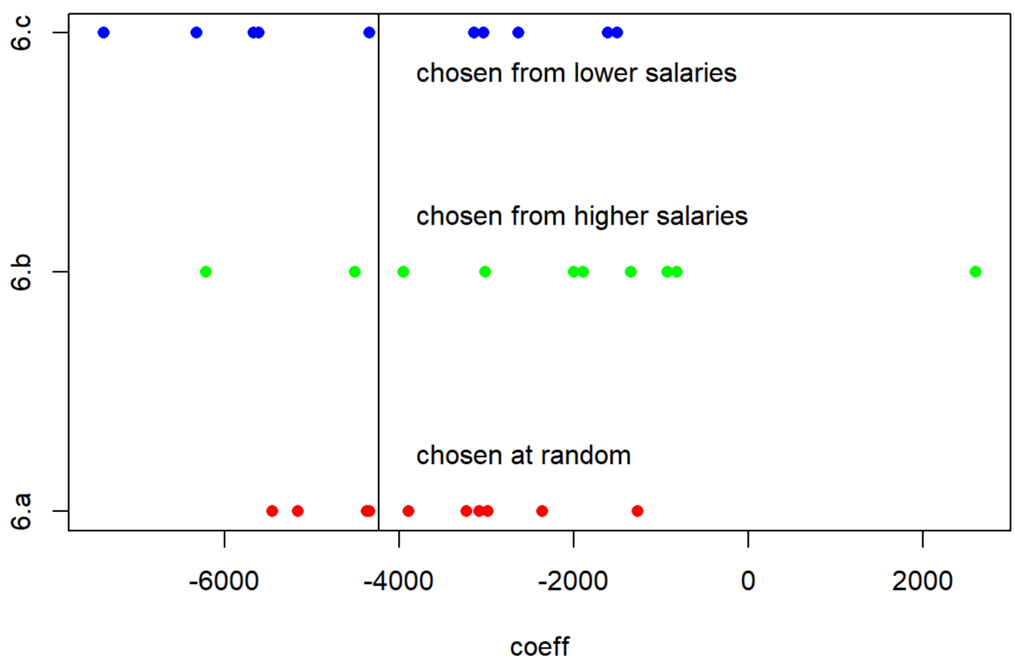

Table A.2: Switch 5 from Unknown to White

	Mixed	Another	Black	EastAsian	Latine	MiddleEast	SouthAsian	SouthEastAsian	Unknown	IndigCan	Female
	-3745.19	-788.05	-3915.10	723.23	-2183.49	141.10	115.54	2202.73	-19.05	-4233.75	-296.37
	-3747.36	-788.58	-3920.70	714.89	-2189.30	133.21	107.38	2196.53	-36.89	-4235.21	-298.94
	-3744.57	-787.72	-3913.59	725.37	-2182.01	143.14	117.64	2204.20	-14.61	-4233.34	-295.78
	-3745.15	-788.05	-3914.94	723.42	-2183.34	141.29	115.71	2202.75	-18.67	-4233.71	-296.34
	-3747.22	-788.44	-3919.93	715.96	-2188.55	134.18	108.44	2197.30	-34.31	-4235.00	-298.50
	-3752.60	-789.42	-3931.17	698.87	-2200.47	117.86	91.95	2184.84	-70.31	-4238.01	-303.81
	-3765.52	-791.69	-3961.74	653.01	-2232.28	74.17	47.02	2151.25	-167.11	-4246.08	-316.66
	-3734.29	-785.91	-3889.16	762.14	-2156.46	178.05	153.48	2231.25	63.00	-4227.07	-285.23
	-3744.24	-787.86	-3912.95	726.47	-2181.23	144.21	118.69	2204.98	-12.25	-4233.11	-295.45
	-3742.33	-787.50	-3908.37	733.35	-2176.45	150.78	125.41	2210.03	2.24	-4231.99	-293.47
Mean Coeff	-3746.85	-788.32	-3918.77	717.67	-2187.36	135.80	110.13	2198.58	-30.80	-4234.73	-298.06
Std Err	2.53	0.47	5.85	8.80	6.12	8.38	8.58	6.45	18.55	1.54	2.55
Ref Coeff	-3747.22	-788.44	-3919.93	715.96	-2188.55	134.18	108.44	2197.30	-34.31	-4235.00	-298.50