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Assessing compensation and organizational variation with imperfect data: An application of count-based indices of variation

Salomon Alcocer Guajardo
BizSavy, Boca Raton, FL, USA.

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ABSTRACT

An accurate assessment of human capital or labor force variation in organizations is predicated upon collecting error-free data. When organizations report imprecise human capital or labor force data, problematic data analytic issues arise because the application of frequency-based indices of variation obtain questionable measures of variation. This article addresses the assessment of vertical pay variation in organizations with count-based indices of heterogeneity. In doing so, this article demonstrates how imprecise categorical pay dispersion data negatively impacts the ability of logarithm-, mode-, and probability-based indices of variation to obtain accurate and reliable measures of pay variation. More importantly, this article demonstrates how count-based indices of variation overcome data analytic issues presented by imprecise data reported by organizations. In demonstrating their appropriateness to assess variation in organizations, the article assesses the measurement validity and reliability of unstandardized and generalized scores of pay dispersion obtained with count-based indices. By applying count-based indices to imprecise pay dispersion data reported by New York City municipal departments, this article addresses an important data analytic issue and shows that count-based indices are a viable alternative method for assessing variation in organizations when imprecise data limit the use of logarithm-, mode-, or probability-based indices. As an alternative method to frequency-based indices of variation, count-based indices provide additional data analytic techniques for assessing how pay and other forms of variation directly or indirectly affect organizational stability and performance.

1. INTRODUCTION

Over the past several decades, research on organizational management and science has focused more intensely on variation in compensation (or pay dispersion) and its effects on organizational performance and workforce stability (Bloom, 1999; Bloom & Michel, 2002; Downes & Choi, 2014; Shaw & Gupta, 2007). Extant research shows that pay dispersion occurs vertically and horizontally in organizations. Vertical variation in compensation occurs when pay disparity (or inequality) exists between low- and high-level job classifications and positions (Conroy, Gupta, Shaw, & Park, 2014; Downes & Choi, 2014; Shaw & Gupta, 2007). Conversely, horizontal (or lateral) variation in compensation occurs when pay disparity exists within similar job classifications and positions (Conroy, Gupta, Shaw, & Park, 2014; Downes & Choi, 2014; Shaw & Gupta, 2007). When vertical and horizontal pay dispersion are analyzed concomitantly, overall compensation variation is assessed across employees and positions by examining the pay disparity between the lowest- and highest-paid employee (Carnahan, Agarwal, & Campbell, 2012; Conroy, Gupta, Shaw, & Park, 2014). Regardless of whether compensation variation is examined horizontally or vertically, pay dispersion exists in nonprofit, private, and public organizations because employees differ with respect to education, employment tenure, experience, job position, and other factors (Bucciol, Foss, & Piovesan, 2014; Conroy, Gupta, Shaw & Park, 2014). Because so few data analytic studies address how to assess compensation, organizational, or workforce variation when imperfect data are reported, this article applies count-based Guajardo indices of variation to salary-related data reported by 71 New York City (NYC) municipal departments for the fiscal year (FY) 2022. In so doing, this article illustrates how reliable and valid measures of variation are obtainable when organizations provide imperfect and imprecise human capital- and labor-based data. As such, this article differs from previous studies on pay dispersion.

Briefly, the assessment of pay dispersion in organizations is important because disparity in compensation amongst employees affects organizational performance and workforce stability (Bloom, 1999; Bloom & Michel, 2002; Bucciol, Foss, & Piovesan, 2014; Caruso, Carlo, & Marco, 2016; Conroy, Gupta, Shaw, & Park, 2014; Shaw & Gupta, 2007; Zhang, He, Park, Xing, & Wu, 2023). For instance, Bloom (1999) found a negative statistical relationship between hierarchical pay dispersion and group performance. When Bucciol, Foss, and Piovesan (2014) measured pay dispersion with the Gini (1921) and Theil (1967) indices, they found that pay dispersion had a negative impact on group performance. By contrast, Caruso, Carlo, and Marco (2016) found that wages were related positively to group performance. However, when Caruso, Carlo, and Marco used the Simpson (1949) index of diversity to measure wage variation, they obtained an inverse relationship between the Simpson scores and group performance. When Shaw, Gupta, and Delery (2002) measured pay dispersion as the difference between a new driver and senior driver in the motor carrier and concrete pipe industries, they obtained significant statistical relationships between pay dispersion and organizational performance. Zhang, He, Park, Xing, and Wu (2023) used the coefficient of variation (CV) to measure pay dispersion amongst employees of Chinese retail stores when they assessed the statistical relationships between pay dispersion, voluntary turnover, and organizational performance. They found that pay-level differences between different functional groups had statistically significant effects on organizational performance. Extant research shows that variation in compensation amongst employees and work groups impacts organizations negatively and positively.

Pay variation in organizations is generally measured with the CV, Gini, or Theil index (Bloom, 1999; Bloom & Michel, 2002; Bucciol, Foss, & Piovesan, 2014; Grabner & Martin, 2020; Shaw, 2015; Shaw & Gupta, 2007; Zhang, He, Park, Xing, & Wu, 2023). In some studies, pay dispersion is measured by obtaining the difference between the lowest and highest paid employee (Shaw, Gupta, & Delery, 2002). Simpson's index of diversity is also used to measure pay variation (Caruso, Carlo, & Marco, 2016).

The use of different indices or methods to quantify pay variation is important because the measures assess different dimensions of variation: disparity, heterogeneity, or separation (Harrison & Klein, 2007; Harrison & Sin, 2006; Stirling, 2007). When the CV, Gini, or Theil indices are used independently or concomitantly to quantify pay inequality amongst employees in an organization or work group, salary disparity is assessed (Harrison & Klein, 2007; Harrison & Sin, 2006; Stirling, 2007). Separation in pay is assessed when the standard deviation or mean Euclidean distance are used to quantify compensation inequality (Harrison & Klein, 2007; Harrison & Sin, 2006). As noted by Harrison and Klein (2007), the application of disparity and separation indices require that the data are continuous. Heterogeneity (or variety) in pay is assessed when the Simpson or Shannon (1948) indices are applied to compensation data reported categorically (Harrison & Klein, 2007; Harrison & Sin, 2006; Stirling, 2007).

The application of disparity, separation, and variety indices of variation require that organizations provide accurate continuous or categorical human capital and labor force data to obtain valid and reliable measures of heterogeneity. When organizations provide error-free continuous or categorical human capital and labor force data, disparity-, logarithm-, mode-, and probability-based indices of variation assess the level of compensation, organizational, and workforce heterogeneity accurately. Conversely, when organizations provide inaccurate or imperfect human capital- and labor-related data, the measures of variation obtained by disparity-, logarithm-, mode-, or probability-based indices are questionable at best.

Imperfect or imprecise human capital (or labor) data impact the application of logarithm-, mode-, and probability-based indices of variation in several ways. First, when group frequencies (or percentages) are imprecise, the application of a logarithm-, mode-, or probability-based indices produce variation scores that contain moderate to high levels of measurement error. Second, the measurement bias inherent in a logarithm-, mode-, or probability-based index of variation is compounded (or magnified) when scores of heterogeneity (or variation) are based on imperfect or imprecise human capital data. Third, depending on the extent to which human capital data are imperfect or imprecise, the application of a logarithm-, mode-, or probability-based indices of variation may be prohibited or severely restricted.

Although the discussion has centered on the negative impacts that faulty human capital data have on the application of logarithm-, mode-, and probability-based indices of variation, imperfect or imprecise labor-related data also have negative impacts on indices of variation that utilize the average or range to obtain measures of heterogeneity. For instance, obtaining accurate deviations from the average becomes problematic when group frequencies are inaccurate. Additionally, inaccurate group frequencies produce an erroneous difference (or range) between the category with the largest frequency and the one with the smallest frequency. Inaccurate and imprecise labor-related data also negatively impact indices of variation that assign weights to categories when they are ranked in a descending order from largest to smallest.

In contrast to Bucciol, Foss, and Piovesan (2014), Caruso, Carlo, and Marco (2016), Grabner and Martin (2020), Shaw (2015), and other similar studies that have assessed compensation (or pay) dispersion with measures of disparity, separation, or variation, this article addresses the question of what data analytic methods are suitable for assessing compensation, demographic, employment, or occupational variation in organizations when accurate and reliable human capital data are not readily available. The discussion begins with presenting imperfect and inaccurate salary-related data reported by 71 NYC municipal departments for FY 2022. In doing so, the article illustrates how flawed salary-related data severely compromise the ability of logarithm-, mode-, and probability-based indices of variation to obtain valid income heterogeneity scores. This discussion is facilitated by applying the logarithm-based Shannon (1948) index, the mode-based Wilcox (1967) index, and the probability-based Simpson (1949) index to the salary-related data. More importantly, the article demonstrates how count-based indices of variation overcome the measurement barriers, limitations, and restrictions presented by flawed salary-related data to obtain unstandardized and generalized measures of variation. Specifically, this article applies count-based Guajardo (2024a) indices of variation to the salary-related data to obtain unstandardized and generalized (or standardized) scores of heterogeneity (or variation). By applying the count-based Guajardo indices of variation to the imperfect and inaccurate salary-related data, this article contributes to the fields of data analytics and of organizational management and science.

The use of the count- and logarithm-based Guajardo indices have implications for research focusing on diversity theory and measurement. By applying the count- and logarithm-based Guajardo indices to categorical-based human capital and labor force data, this article contributes to the measurement of organizational and workforce diversity. It does so by illustrating how to obtain measures of variation with count-based indices of variation when organizations provide imprecise human capital data and when such data prohibit the application of the CV, Gini, Shannon, Simpson, or Theil indices. This article also expands on the assessment of diversity as variety by providing complimentary indices to the index of qualitative variation (IQV; Mueller & Schuessler, 1961; Wilcox, 1967), Shannon, and Simpson indices (Guajardo, 2024a). With respect to this article's implications for diversity theory, the application of the count- and logarithm-based Guajardo indices are likely to detect statistical relationships amongst organizational-based predictors and the measures of variation that differ from those obtained with the Shannon or Simpson indices when they are applied to the same data (Guajardo, 2024b and 2024c). To this end, the application of the count-based and logarithm-based Guajardo indices may support or contradict the findings of previous studies that have assessed organizational and workforce variation. As noted by Caruso, Carlo, and Marco (2016), the use of different indices of diversity lead to different statistical findings.

A. NYC Human Capital and Labor Force Data

NYC's Department of Citywide Administrative Services (DCAS) provides human capital and labor force data for 71 municipal departments annually. The human capital data include information about the age, ethnicity, and gender of municipal employees. Labor force data include information about civil service job classifications, salaries, and years of service. The data also include information about the number of new hires, the number of retirements, and the number of resignations. While the human capital and labor force data provided by DCAS are useful for assessing and understanding general municipal labor trends, the data reported by NYC municipal departments are imperfect and inaccurate, prohibiting the ability to develop accurate, compatible, reliable, and valid human capital- and labor-based benchmarks and key performance indicators (KPIs). In particular, the imperfect and inaccurate human capital and labor force data present obstacles for assessing and benchmarking the demographic, employment, and occupation diversity trends of NYC municipal departments.

Table 1 presents the salary-related data reported by the NYC Conflicts of Interest Board (CIB) and NYC Landmarks Preservation Commission (LPC) for FY 2022 (DCAS, 2024). According to CIB, eight employees have annual salaries above $120,000 (see Panel A). Fewer than five employees have annual salaries between $110,000 and $120,000. Because the data for the $110k - $120k salary band are imprecise, the actual number of employees in the salary band is unknown. Similarly, the actual number of employees in the $90k - $100k salary band is unknown. According to CIB, fewer than five employees have annual salaries between $90,000 to $100,000. The salary-related data for the remaining salary bands show the identical information where fewer than five employees have annual salaries within the specified salary range. Because CIB reported imprecise salary-related data, the total number of employees in the workforce is unknow. Based on other data contained in the DCAS report for FY 2022, CIB had a labor force composed of 26 employees.

Table 1. Annual employee compensation for CIB and LPC for FY 2022

A. CIB salary distribution for FY 2022

Salary Category (k)	Salary Band	Reported Frequency (f)	Reported Percentage (p)	Estimated Frequency (f)
1	$120k+	8	0.31	8.1
2	$110k to 120k	<5	0.12	3.1
3	$100k to 110k			
4	$90k to 100k	<5	0.12	3.1
5	$80k to 90k	<5	0.04	1.0
6	$70k to 80k	<5	0.12	3.1
7	$60k to 70k	<5	0.12	3.1
8	$50k to 60k	<5	0.15	3.9
9	$40k to 50k	<5	0.04	1.0
10	<40k			
Total		26	1.02	26.5

B. LPC salary distribution for FY 2022

Salary Category (k)	Salary Band	Reported Frequency (f)	Reported Percentage (p)	Estimated Frequency (f)
1	$120k+	8	0.11	8.1
2	$110k to 120k	<5	0.03	2.2
3	$100k to 110k	<5	0.04	3.0
4	$90k to 100k	<5	0.05	3.7
5	$80k to 90k	8	0.11	8.1
6	$70k to 80k	18	0.24	17.8
7	$60k to 70k	21	0.28	20.7
8	$50k to 60k	5	0.07	5.2
9	$40k to 50k	<5	0.05	3.7
10	<40k	<5	0.01	0.7
Total		74	0.99	73.3

Source: DCAS. (2024). *Fiscal Year 2022 New York City government workforce profile report*. New York City Department of Citywide Administrative Services.

The data reported by CIB also provide imprecise information with respect to the percentages corresponding to each salary band (or category; see Table 1, Panel A). Due to CIB not reporting the total number of employees in the labor force, the accuracy of the percentages is questionable and tenuous. When the percentages are summed, a total of 102% is obtained and seems to be due to more than a simple rounding error. Additionally, when the percentage associated with each salary band (or category) is applied to the CIB labor force of 26 employees, inaccurate estimates of the number of employees in each salary category are obtained. The extent of the inaccuracy of each estimate is unknown because the salary-related data reported by CIB are imperfect and imprecise.

Based on the salary-related data reported the LPC for FY 2022, the data analytics and measurement errors are more acute (see Table 1, Panel B). While LPC provides data for each salary category, 50% of the categories contain imprecise frequency data. For instance, LPC reported that fewer than five employees have annual salaries between \$110,00 and \$120,000. Similarly, LPC reported that fewer than five employees have annual salaries between \$100,000 and \$110,000. The same holds true for the frequency for the \$90,000 to \$100,000 salary band. The DCAS report indicates that LPC had a labor force of 74 employees in FY 2022.

In addition to LPC reporting imprecise frequencies for multiple salary categories, the department reported imprecise percentages for each salary category (see Table 1, Panel B). When the salary category percentages are summed, a total of 99% is obtained. Because LPC did not provide the frequency data associated with each salary category, the source of the measurement error or imprecision in not readily known.

The imperfect (or imprecise) percentage data reported by LPC leads to an underestimation of the number of employees in each salary category (see Table 1, Panel B). As Panel B shows, LPC reported that 21 employees had annual salaries between \$60,000 and \$70,000 in FY 2022. However, when the percentage reported for the salary band is applied to the LPC workforce of 74 employees, an estimate of 20.7 employees is obtained. For the salary category of under \$40,000, an estimate of less than one employee is obtained when the percentage for the category is applied to the total labor force of 74 employees. When the estimates are summed, a total workforce of 73.3 employees is obtained. Stated simply, the imprecise percentages contribute to underreporting the total number of employees in the LPC labor force.

Due to the imperfection and imprecision of the data reported by CIB and LPC, the salary-related data negatively impact the application of logarithm-, mode-, and probability -based indices of variation. The negative impacts of the flawed salary-related data include the following:

- Inaccurate estimates of distribution parameters for diversity scores and human capital- and labor-based KPIs;
- Low to moderate levels of construct and measurement validity amongst diversity scores and human capital- and labor-based KPIs;
- Measurement incompatibility of diversity scores and human capital- and labor-based KPIs between NYC municipal departments; and,
- Moderate to high levels of measurement error amongst diversity scores and human capital- and labor-based KPIs.

Although this article focuses exclusively on the data analytic and measurement issues associated with the application of indices of variation to the salary-related data reported by NYC municipal departments, the issues apply equally to other human capital and labor data contained in the DCAS report for FY 2022.

A review of annual reports from 2014 to 2024 shows that DCAS has consistently reported imprecise human capital and labor force data. As Table 1 shows, DCAS uses <5 when frequencies are below 5 and uses <1% for percentages below 1%. The methodological section of the DCAS reports fail to state the reasons for not reporting frequencies below 5 or percentages below 1%. De Veaux and Hand (2005) and McCausland (2021) observe that poor quality data occur for the following reasons:

1. Data are bad at the source,
2. Data are inherently biased, or,
3. Data are distorted or manipulated.

Data distortion, poor definition rules, and inadequate quality control protocols are likely to be the reasons for DCAS including imperfect and imprecise human capital and labor force data in the annual reports.

2. Literature Review

The Shannon (1948; H) index of diversity is the most frequently used logarithm-based index when heterogeneity is assessed in organizations (Alexander, Nuchols, Bloom, & Lee, 1995; Choi & Rainy, 2010; Biemann & Kearney, 2010). As developed by Shannon (1948), H obtains unstandardized scores and is defined as follows (see Table 2): $H = -\Sigma p \ln(p)$. The maximum H (H_M) score possible for a qualitative demographic or human capital-based characteristic is determined by the logarithm of the total number of attributes of the characteristic ($\ln(k)$; Pielou, 1966). Accordingly, when an unstandardized H score is divided by $\ln(k)$ or is multiplied by the reciprocal of $\ln(k)$, a generalized H (H_G) score of diversity is obtained (Pielou, 1966). Because H_G scores obtain the proportion of the maximum amount of diversity possible, H_G scores range from 0 to 1. A score of 0 indicates the absolute absence of heterogeneity; a score of 1 indicates the attainment of perfect heterogeneity (Guajardo, 2023a). Each H_G score also indicates the proportion of the maximum level of diversity possible that was attained.

Table 2. Generalized and unstandardized indices of diversity

Index	Measure of Diversity	Maximum Level of Diversity	Generalized Index of Diversity	Source
G	$\frac{\Sigma k - 1}{\ln\sqrt{N}}$	$\frac{K - 1}{\ln\sqrt{N}}$	$\left(\frac{\ln\sqrt{N}}{K-1}\right)\left(\frac{\Sigma k - 1}{\ln\sqrt{N}}\right)$	Guajardo, 2024a
G_{LN}	$\frac{\ln\Sigma k}{\ln\sqrt{N}}$	$\frac{\ln K}{\ln\sqrt{N}}$	$\left(\frac{\ln\sqrt{N}}{\ln K}\right)\left(\frac{\ln\Sigma k}{\ln\sqrt{N}}\right)$	Guajardo, 2024a
H	$-\Sigma p\ln(p)$	$\ln(k)$	$\frac{-\Sigma p\ln(p)}{\ln(k)}$	Pielou, 1966 Shannon, 1948
			$\left(\frac{1}{\ln k}\right) - \Sigma p\ln(p)$	
S	Σp^2	$\frac{k-1}{k}$ or $1 - \frac{1}{k}$	$\frac{1 - \Sigma p^2}{\left(\frac{k-1}{k}\right)}$	Lieberson, 1969 Simpson, 1949
			$\left(\frac{k}{k-1}\right)(1 - \Sigma p^2)$	Agresti & Agresti, 1978
W_M	$Kp_M - 1$	$K - 1$	$1 - \left[\left(\frac{1}{K-1}\right)(Kp_M - 1)\right]$	Wilcox, 1967

Note: k = the number of attributes of a qualitative demographic characteristic; K = the total number of attributes created for a qualitative demographic characteristic; ln = the natural logarithm of a number; M = mode; N = the total number of individuals in an assemblage; p = the percentage (or proportion) of individuals in each category based on N.

Like the Shannon index, the Simpson (1949; S) index is the most frequently used probability-based index when heterogeneity is assessed in organizations (Biemann & Kearney, 2010; Bossert, D'Ambrosio, & La Ferrara, 2011; Harrison & Klein, 2007). As a probability-based index, the Simpson index obtains the probability that two individuals chosen randomly from an assemblage will belong to the same group (Simpson, 1949). To obtain the probability that two individuals will belong to a different group, the Simpson concentration score (S_C) is subtracted from 1 as follows (see Table 2): $S_D = 1 - \Sigma p^2$. When S_D is divided by the maximum level of diversity possible ($S_M = \frac{k-1}{k}$) or is multiplied by the reciprocal of S_M ($S_M^{-1} = \frac{k}{k-1}$), a generalized S_D (S_{DG}) is obtained (Agresti & Agresti, 1973; Guajardo, 2023b and 2023c; Lieberson, 1969). The distribution of S_{DG} scores ranges from 0 to 1 where a score of 0 indicates the absolute absence of heterogeneity and a score of 1 indicates perfect heterogeneity (Guajardo, 2023a and 2023b). Like the H_G score discussed previously, each SDG score indicates the proportion of the maximum level of diversity possible that was attained.

In contrast to the use of the Shannon and Simpson indices, the use of mode-based indices of variation in the assessment of heterogeneity in organizations is rare. Guajardo (2023c) used the mode-based Hussain-Khan (2019) diversity index to assess demographic diversity in NYC departments for FY 2019. Briefly, the generalized Hussain-Khan diversity index is defined as follows: $D_{HK} = \left(\frac{1}{k-1}\right)\left(\frac{1}{p_M} - 1\right)$. In this article, the mode-based Wilcox (1967; WM) index of diversity is used because D_{HK} obtains low generalized diversity scores when compared to the measures obtained with the Shannon and Simpson indices (Guajardo, 2023a, 2023b, and 2023c). As Table 2 shows, the generalized W_M (W_{MG}) index is defined as follows: $W_{MG} = 1 - \left[\left(\frac{1}{K-1}\right)(Kp_M - 1)\right]$. Like the generalized Shannon and Simpson indices, W_{MG} ranges from 0 to 1 where a score of 0 indicates the absolute absence of heterogeneity and a score of 1 indicates the attainment of perfect heterogeneity (Wilcox, 1967).

Recent studies on organizational heterogeneity have used count- and logarithm-based Guajardo indices of variation (Guajardo, 2024a and 2024c). The count-based Guajardo (G) index obtains generalized and unstandardized scores of variation (see Table 2). Unstandardized G scores are obtained by assigning a value of 1 to categories with at least one employee, summing the categories with a value of 1 (Σk), subtracting 1 from Σk (Σk - 1), and then dividing $\Sigma k - 1$ by the natural logarithm of the square root of the total number of individuals in the assemblage ($\ln\sqrt{N}$). The formula for obtaining a G score is as follows: $\frac{\Sigma k-1}{\ln\sqrt{N}}$. For a particular assemblage, the maximum G score (G_M) possible is determined by the total number of categories for the human capital-based characteristic (K) and the total number of individuals (N). As illustrated in Table 2, the formula for G_M is as follows: $G_M = \frac{K-1}{\ln\sqrt{N}}$. When G is multiplied by the reciprocal of G_M, a generalized G (G_G) score is obtained as follows: $G_G = \left(\frac{\ln\sqrt{N}}{K-1}\right)\left(\frac{\Sigma k-1}{\ln\sqrt{N}}\right)$. Like the H_G, S_{DG}, and W_{MG} indices discussed previously, the distribution of G_G scores ranges from 0 to 1 and indicate the degree to which an organization or its labor force is heterogeneous. Each G_G score also indicates the proportion of the maximum level of diversity possible that was attained.

The logarithm-based Guajardo (2024a and 2024c; G_{LN}) index compliments the count-based G index (see Table 2). In contrast to the G index, G_{LN} calculates an unstandardized diversity score by obtaining the natural logarithm of the sum of categories with a value of 1 (lnΣk) and then dividing lnΣk by the natural logarithm of the square root of the total number of individuals in the assemblage ($\ln\sqrt{N}$). As indicated in Table 2, G_{LN} is defined as follows: $G_{LN} = \frac{\ln\Sigma k}{\ln\sqrt{N}}$. The maximum G_{LN} (G_{LNM}) score for an organization is determined by the natural logarithm of the total number of categories of the human capital-based characteristic (lnK) and $\ln\sqrt{N}$. As shown in Table 2, a G_{LNM} score is obtained as follows: $G_{LNM} = \frac{\ln K}{\ln\sqrt{N}}$. Like the diversity indices discussed previously, G_{LN} obtains a generalized diversity score (G_{LNG}) when an unstandardized score is divided by the maximum diversity score possible (G_{LNM}) or is multiplied by the reciprocal of G_{LNM}. For G_{LN}, a G_{LNG} score is calculated as follows: $G_{LNG} = \left(\frac{\ln\sqrt{N}}{\ln K}\right)\left(\frac{\ln \Sigma k}{\ln\sqrt{N}}\right)$. Consistent with the diversity indices discussed previously, G_{LNG} scores range from 0 to 1 and indicate the proportion of the maximum level of diversity possible that was attained. Additionally, a score of 0 indicates that absolute absence of heterogeneity and a score of 1 indicates perfect heterogeneity.

A. *Application of Diversity Indices*

The data analytics and measurement issues associated with applying the Shannon (H), Simpson (S), and Wilcox (W_M) indices to the imprecise salary-related data reported by CIB and LPC for FY 2022 are summarized in Table 3. Due to the lack of data specificity, an H score is incalculable for CIB (see Panel A). In addition, the lack of data specificity with respect to the frequency data associated with each category prohibits the application of the S index. Although the percentage of each salary category is reported by CIB, inaccurate SD and SG scores are obtained. Based on the CIB data, a Simpson homogeneity score (SC) of 0.179 is obtained, suggesting that there is an 18% probability that 2 individuals selected randomly would have the same annual income. The SD score of 0.821 (SD = 1 – 0.179) suggests a high level of vertical income variation amongst the CIB labor force. Additionally, the SD score suggests that there is an 82% probability that 2 individuals selected randomly would have different annual incomes. The SG score of 0.912 suggests that CIB attained 91% of the maximum level of income variation possible for FY 2022. When compared to the SD and SG scores obtained by NYC municipal departments with accurate frequency and percentage data for each salary band, the SD and SG measures obtained for CIB are biased and incompatible because the scores misrepresent (or misstate) the level of income variation.

Table 3. Scores of variations for annual employee compensation for CIB and LPC for FY 2022

A. Income diversity for CIB for FY 2022

Salary Category (k)	Salary Band	Reported Frequency (f)	Reported Percentage (p)	p^2	p*ln(p)	Count of k
1	\$120k+	8	0.31	0.096	-0.363	1
2	\$110k to 120k	<5	0.12	0.014	-0.254	1
3	\$100k to 110k			0.000	#NUM!	
4	\$90k to 100k	<5	0.12	0.014	-0.254	1
5	\$80k to 90k	<5	0.04	0.002	-0.129	1
6	\$70k to 80k	<5	0.12	0.014	-0.254	1
7	\$60k to 70k	<5	0.12	0.014	-0.254	1
8	\$50k to 60k	<5	0.15	0.023	-0.285	1
9	\$40k to 50k	<5	0.04	0.002	-0.129	1
10	<40k			0.000	#NUM!	
Total (Σ)	Total	26	1.02	0.179	#NUM!	8

S_C =	0.179	G =	4.297
S_D =	0.821	G_S =	0.778
S_S =	0.912	G_{LN} =	1.276
H =		G_{LNS} =	0.903
W_M =	2.080		
W_{MS}	0.769		

B. Income diversity for LPC for FY 2022

Salary Category (k)	Salary Band	Reported Frequency (f)	Reported Percentage (p)	p^2	p*ln(p)	Count of k
1	$120k+	8	0.11	0.012	-0.243	1
2	$110k to 120k	<5	0.03	0.001	-0.105	1
3	$100k to 110k	<5	0.04	0.002	-0.129	1
4	$90k to 100k	<5	0.05	0.003	-0.150	1
5	$80k to 90k	8	0.11	0.012	-0.243	1
6	$70k to 80k	18	0.24	0.058	-0.343	1
7	$60k to 70k	21	0.28	0.078	-0.356	1
8	$50k to 60k	5	0.07	0.005	-0.186	1
9	$40k to 50k	<5	0.05	0.003	-0.150	1
10	<40k	<5	0.01	0.000	-0.046	1
Total (Σ)	Total	74	0.99	0.173	-1.950	10

S_C =	0.173	G =	4.182
S_D =	0.827	G_S =	1.000
S_S =	0.919	G_{LN} =	1.070
H =	1.950	G_{LNS} =	1.000
H_S	0.847		
W_M =	1.810		
W_{MS}	0.799		

Source: DCAS. (2024). *Fiscal Year 2022 New York City government workforce profile report* . New York City Department of Citywide Administrative Services.

When the mode-based W_M index is applied to the data reported by CIB, an unstandardized score of 2.08 (W_M = 2.08) is obtained and suggests a moderate level of vertical income variation (Table 3, Panel A). The generalized W_M score of 0.77 (W_{MS} = 0.769) suggests that CIB attained 77% of the maximum level of income variation possible for FY 2022. In addition, the generalized score suggests that the CIB labor force is distributed moderately well across the salary band categories. However, due to the inaccuracy of the percentage associated with each salary category, the W_M and W_{MS} scores for income variation are inaccurate and may overstate the level of income variation in the CIB labor force.

In contrast to the H, S, and W_M indices, the count- and logarithm-based Guajardo indices of variation obtain scores of vertical income heterogeneity by disregarding each salary category frequency and percentage and assigning a value of 1 to each category with at least one employee (see Table 3, see Panel A). In so doing, the pay dispersion scores obtained by the Guajardo indices are not influenced by the imprecise data and provide better estimates of the level of income heterogeneity in the CIB labor force. Based on the CIB salary band data, a G score of 4.30 (G = 4.297) is obtained and indicates a moderately high level of income variation. The generalized G score of 0.78 (G_S = 0.778) indicates that CIB attained 78% of the maximum level of income variation possible. When the G_{LN} index is applied to the same data, an unstandardized score of 1.28 (G_{LN} = 1.276) is obtained and indicates a moderately high level of vertical income variation. The generalized G_{LN} score of 0.90 (G_{LNS} = 0.903) also indicates a high attainment of income dispersion. Specifically, the score indicates that CIB attained 90% of the maximum level of income variation possible.

Due to LPC's imprecise reporting of the number of employees and the percentage in each salary category, the S index underestimates the level of vertical income variation that exists in the labor force (see Table 3, Panel B). In practical terms, the probability-based scores are questionable due to the inaccurate percentages. Based on the S_C score of 0.17 (S_C = 0.173), income homogeneity (or similarity) is low in the LPC labor force. The S_D score of 0.83 (S_D = 0.827) suggests that there is an 83% probability that 2 employees selected randomly will have the same annual income. The S_S score of 0.92 (S_S = 0.919) suggests that LPC attained 92% of the maximum level of income variation possible. In addition, the generalized score suggests that the LPC labor force is distributed evenly across the salary bands. While the Simpson scores overestimate the level of income variation in the CIB labor force, they underestimate the level of income variation in the LPC labor force.

The mode-based W_M index also obtained questionable scores of vertical income variation for LPC (see Table 3, Panel B). An unstandardized W_M score of 1.81 (W_M = 1.81) was obtained when the index was applied to the mode of

28%. A generalized W_{MS} score of 0.80 (W_{MS} = 0.799) was obtained, suggesting that LPC attained 80% of the maximum level of income variation possible. The generalized score also suggests that the LPC labor force is distributed moderately well across the salary bands. Because of the imprecision of the salary-related data, the percentage associated with the salary category of $60,000 to $70,000 may be lower or higher than the 28% reported by LPC. If the percentage is higher, the mode-based Wilcox index underreports the level of income variation in the labor force. Conversely, if the percentage is lower than 28%, the index overreports the level of income variation.

Due to the count- and logarithm-based Guajardo indices ignoring the frequencies and percentages reported for each salary category by LPC when obtaining the income variation scores, the G and G_{LN} indices obtained identical generalized scores of 1.00 (G_S and G_{LNS} = 1.00) for the department (see Table 3, Panel B). The generalized G_S and G_{LNS} scores indicate that LPC attained 100% of the maximum level of income variation possible. More importantly, the G_S and G_{LNS} scores indicate that LPC attained a high level of income equitability across the salary bands. Put differently, LPC employees are distributed evenly across the department's salary structure. Although the LPC salary data is imperfect and imprecise, the G and G_{LN} indices obtained income variation scores with a higher level of accuracy.

3. Methodology

NYC was selected for this study because the city's governmental structure is composed of diverse public organizations, ranging from the largest to the smallest municipal departments in the United States (US). As the largest municipal government in the US, NYC offers public services that include education to the licensure and oversight of taxi services. The NYC Department of Education (NYCDOE) is the largest local school district in the US with 995,000 students, 1,800 schools, and 140,000 employees (Abdulkadiroglu, Pathak, and Roth, 2005). Additionally, the NYC Police Department (NYPD) is the largest municipal police organization in the US with 34,000 police officers and 20,000 civilians (Guajardo, 2016; Raganella & White, 2004). The NYC Fire Department (FDNY) is the largest municipal fire department in the US with 11,000 fire fighters, 4,000 emergency medical services (EMS) employees, and 2,000 civilians. By contrast, the NYC Municipal Water Finace Authority (MWFA) is composed of 11 employees. In many US municipal governments, education and other services are administered independently of the central government. For this study, the sample consists of 71 NYC departments that collect and report human capital and labor force data on its employees annually.

Unlike many municipal governments in the US, NYC departments have provided readily accessible human capital and labor force data for public use for over a decade. The NYC Department of Citywide Administrative Services (DCAS) issues an annual report containing organization and workforce data gathered from 71 departments which include the number of full- and part-time employees, the number of employees eligible for retirement, the number of men and women employees, and the percentage of union members. The DCAS annual report also contains salary (or compensation) data pertaining to full-time employees. In addition, DCAS provides financial data gathered from NYC municipal departments. For consistency with previous studies (Guajardo, 2023a, 2023b, and 2023c), this article uses human capital data reported by DCAS for FY 2022.

Because NYC is the most populous city in the US with 8.5 million residents living in five boroughs (Brooklyn, Bronx, Manhattan, Queens, and Staten Island) and is composed of the largest municipal departments, the generalizability of the findings is limited to cities like Los Angeles, California, and counties like the County of Los Angels, California. The extent to which the findings are generalizable to comparable cities and counties also depends on the size, structure, and services provided by the departments in those cities and counties. In addition, the generalizability of the findings depends on the type of human capital and labor force data that are collected by the municipal departments in the comparable cities and counties.

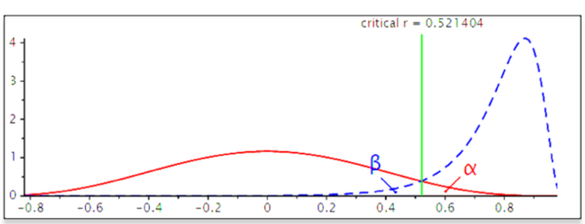
Consistent with Table 3, the count- and logarithm-based Guajardo indices of variation were applied to the salary-related data reported by 71 NYC departments for FY 2022. Obtaining an accurate count of the categories with at least one employee (Σk) for each department was facilitated by replacing “<5” with “1” (see Appendix A). Due to the departments excluding the total number of employees (N) in the labor force from the salary-related data, $\ln \sqrt{N}$ was calculated based on the total number of employees (N) that DCAS reported for each department for FY 2022. Unstandardized and generalized G and GLN scores of income variation were obtained for each NYC department with the methods used in Table 3.

Several statistical methods were used to analyze the unstandardized and generalized G and G_{LN} scores of income variation. Descriptive statistics were used to obtain measures of central tendency and variation. The coefficient of variation (CV) was used to assess the measurement variability of each distribution of scores and to assess the discriminatory power of the indices in detecting subtle differences in the level of vertical income variation amongst the 71 NYC departments. Assessing whether each distribution of scores satisfied the assumption of normality called for the use of the Shapiro-Wilk test at $\alpha = 0.05$. Pearson correlation and principal component analyses were performed to assess construct and measurement validity (Guajardo, 2024d; Meyer, 2010; Meyer & Glenz, 2013; Taylor, 2013). Due to the G and G_{LN} indices obtaining income variation scores based on the same salary-related data, oblique oblimin rotation was used in the PCA (Brown, 2006). Parallel PCA analysis was also used to assess whether the indices measured the same dimension of income variation (Brown, 2006). Lastly, Cronbach's α, greater lower bound, and inter-item correlation coefficients were used to assess the measurement reliability of the income variation scores obtained with the G and G_{LN} indices (Meyer, 2010).

When the measurement validity or reliability of an index is assessed with correlation analysis, a correlation coefficient between 0.70 and 0.90 ($0.70 \leqslant r \geqslant 0.90$) is sufficient (Hair, Hult, Ringle, and Sarstedt, 2022). A two-tail power analysis was performed for the measurement validity and reliability assessment with Cronbach's α and Pearson correlation coefficients set at 0.80 ($r = 0.80$; see Table 4). The analysis was performed at $\alpha = 0.05$ with the power threshold set at 0.95. A correlation coefficient of -0.55 ($r = -0.553$) was obtained for the low critical value. For the upper critical value, a correlation coefficient of 0.55 ($r = 0.553$) was obtained. The power analysis indicated that a sample of 13 cases was sufficient to obtain measurement validity and reliability coefficients of $r = 0.80$ at $\alpha = 0.05$. In this article, the sample consists of 71 NYC departments.

Table 4. Power analysis for measurement reliability

Assessment criteria	Parameter	Output	Parameter
Tail(s)	2	Lower critical r	-0.553
Correlation r (H_1)	0.80	Upper critical r	0.553
α (Error probability)	0.05	Total sample size	13
Power (1-β error probability)	0.95	Actual power	0.951
Correlation r (H_0)	0.00		



4. ANALYSIS

Table 5 summarizes the count- and logarithm-based G scores for each NYC municipal department for FY 2022. The third column contains the total labor force (or headcount) of each department that was reported by DCAS. Consistent with Table 2 and 3, each department's headcount was used to obtain the denominator ($\ln\sqrt{N}$) for the G and G_{LN} indices due to the departments excluding the information when they reported the salary-related data. The fourth column contains the maximum diversity score obtainable by the count-based G index for each department. The unstandardized G scores for income variation are reported in the fifth column. Generalized G scores (G_G) are reported in the sixth column. For consistency, the maximum income variation score obtainable by the logarithm-based G_{LN} index for each department is reported in the seventh column. The eighth column contains the unstandardized G_{LN} income variation scores for each department. Generalized G_{LN} (G_{LNG}) scores are reported in the final column (see table 5).

A. Summary Statistics

The descriptive statistics for the unstandardized and generalized G and G_{LN} income variation scores are presented in Table 6. When the G index was applied to the salary-related data reported by NYC municipal departments for FY 2022, the index obtained an unstandardized maximum diversity score of 4.83 ($G = 4.829$) and an unstandardized minimum diversity score of 1.52 ($G = 1.519$). The mean G score was 2.96 ($\bar{x}G = 2.959$) with a standard deviation of 0.79 ($\sigma G = 0.793$). The Shapiro-Wilk test for normality indicates that the unstandardized G scores are normally distributed at $\alpha = 0.05$ ($W = 0.966$, $p = 0.054$).

By contrast, the distribution of G_G diversity scores is negatively skewed (Skewness = -1.754) with positive kurtosis (Kurtosis = 2.552) and violates the assumption of normality ($W = 0.649$, $p < 0.001$; see Table 6). The maximum G_G score is 1 ($G_G = 1.000$); the minimum G_G score is 0.44 ($G_G = 0.444$). Based on the findings, the mean G_G score is 0.93 ($\bar{x}_{GG} = 0.925$) with a standard deviation of 0.128 ($\sigma_{GG} = 0.128$).

At $\alpha = 0.05$, the distribution of unstandardized G_{LN} diversity scores is positively skewed (Skewness = 0.728) with positive kurtosis (Kurtosis = 0.083) and violates the assumption of normality ($W = 0.948$, $p = 0.005$; see Table 6). A maximum diversity score of 1.57 ($G_{LN} = 1.566$) and a minimum diversity score of 0.39 ($G_{LN} = 0.389$) are obtained when the G_{LN} index is applied to the salary-related data. The mean G_{LN} score is 0.81 ($\bar{x}_{GLN} = 0.810$) with a standard deviation of 0.26 ($\sigma_{GLN} = 0.264$).

Like the distribution of G_G income variation scores, the distribution of generalized G_{LNG} scores is negatively skewed (Skewness = -2.132) with positive kurtosis (Kurtosis = 4.875) and violates the assumption of normality ($W = 0.626$, $p < 0.001$; see Table 6). Consistent with the G index, the G_{LN} index obtained a maximum generalized score of 1.00 ($G_{LNG} = 1.000$).

However, G_{LN} obtained a minimum generalized score of 0.699 ($G_{LNG} = 0.699$). The mean G_{LNG} score is 0.97($\bar{x}_{GLNG} = 0.966$) with a standard deviation of 0.06 ($\sigma_{GLNG} = 0.062$).

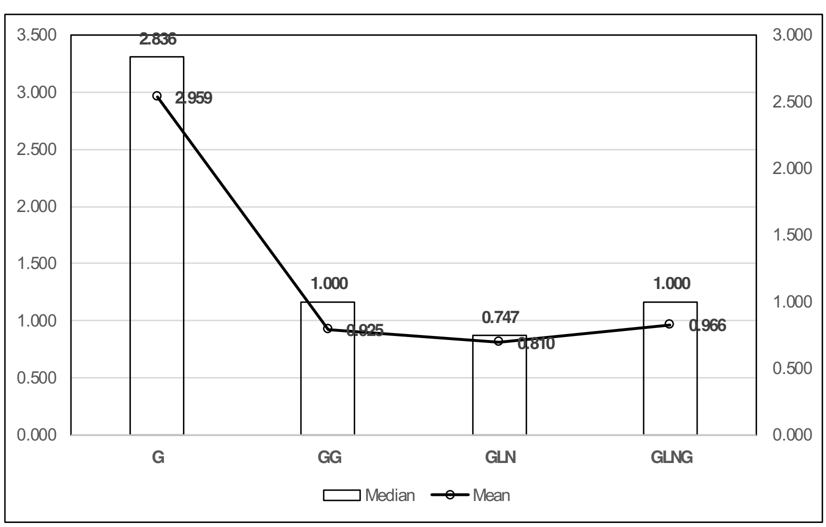
Table 5. G and G_{LN} income diversity scores for NYC municipal departments for FY 2022

			Indices					
Case	NYC Department	Headcount	G_M	G	G_G	G_{LNM}	G_{LN}	G_{LNG}
1	Administration For Children's Services	6857	2.038	2.038	1.000	0.521	0.521	1.000
2	Board Of Correction	23	5.741	3.827	0.667	1.469	1.241	0.845
3	Board Of Election	897	2.647	2.647	1.000	0.677	0.677	1.000
4	Borough President-Bronx	92	3.981	3.981	1.000	1.018	1.018	1.000
5	Borough President-Brooklyn	103	3.884	3.884	1.000	0.994	0.994	1.000
6	Borough President-Manhattan	90	4.000	4.000	1.000	1.023	1.023	1.000
7	Borough President-Queens	109	3.837	3.837	1.000	0.982	0.982	1.000
8	Borough President-Staten Is	44	4.757	4.228	0.889	1.217	1.161	0.954
9	Business Integrity Commission	75	4.169	3.706	0.889	1.067	1.018	0.954
10	Campaign Finance Board	119	3.766	3.766	1.000	0.964	0.964	1.000
11	City Commission On Human Rights	111	3.822	3.822	1.000	0.978	0.978	1.000
12	Civilian Complaint Review Board	245	3.272	2.908	0.889	0.837	0.799	0.954
13	Conflicts Of Interest Board	26	5.525	4.297	0.778	1.413	1.276	0.903
14	Department For The Aging	322	3.117	3.117	1.000	0.797	0.797	1.000
15	Department Of Citywide Admin Svcs	2113	2.351	2.351	1.000	0.602	0.602	1.000
16	Department Of Buildings	1605	2.439	2.439	1.000	0.624	0.624	1.000
17	Department Of City Planning	287	3.181	2.474	0.778	0.814	0.735	0.903
18	Department Of Consumer And Worker Protection	422	2.978	2.978	1.000	0.762	0.762	1.000
19	Department Of Correction	8996	1.977	1.977	1.000	0.506	0.506	1.000
20	Department Of Cultural Affairs	79	4.120	3.662	0.889	1.054	1.006	0.954
21	Department Of Design & Construction	1151	2.554	2.554	1.000	0.653	0.653	1.000
22	Department Of Education	140383	1.519	1.519	1.000	0.389	0.389	1.000
23	Department Of Environment Protection	5733	2.080	2.080	1.000	0.532	0.532	1.000
24	Department Of Finance	1823	2.397	2.397	1.000	0.613	0.613	1.000
25	Department Of Health/Mental Hygiene	6468	2.051	2.051	1.000	0.525	0.525	1.000
26	Department Of Homeless Services	1974	2.372	2.372	1.000	0.607	0.607	1.000
27	Department Of Investigation	295	3.165	3.165	1.000	0.810	0.810	1.000
28	Department Of Parks & Recreation	6805	2.040	2.040	1.000	0.522	0.522	1.000
29	Department Of Probation	1009	2.602	2.602	1.000	0.666	0.666	1.000
30	Department Of Records & Info Service	61	4.379	4.379	1.000	1.120	1.120	1.000
31	Department Of Sanitation	9748	1.960	1.960	1.000	0.501	0.501	1.000
32	Department Of Small Business Services	262	3.233	2.514	0.778	0.827	0.747	0.903
33	Department Of Transportation	5779	2.078	2.078	1.000	0.532	0.532	1.000
34	Department Of Youth & Community Development	506	2.891	2.891	1.000	0.740	0.740	1.000
35	District Attorney - Bronx County	983	2.612	2.612	1.000	0.668	0.668	1.000
36	District Attorney - Kings County	1163	2.550	2.550	1.000	0.652	0.652	1.000
37	District Attorney - Manhattan	1532	2.454	2.454	1.000	0.628	0.628	1.000
38	District Attorney - Queens County	811	2.687	2.687	1.000	0.688	0.688	1.000
39	District Attorney - Richmond County	214	3.354	2.982	0.889	0.858	0.819	0.954
40	District Attorney - Special Narcotics	198	3.404	3.026	0.889	0.871	0.831	0.954
41	Equal Employment Practices Commission	12	7.244	4.829	0.667	1.853	1.566	0.845
42	Financial Information Services Agency	406	2.997	2.997	1.000	0.767	0.767	1.000
43	Fire Department	17712	1.840	1.840	1.000	0.471	0.471	1.000
44	Housing Preservation & Development	2323	2.322	2.322	1.000	0.594	0.594	1.000
45	Human Resources Administration	11364	1.928	1.928	1.000	0.493	0.493	1.000
46	Independent Budget Office	34	5.104	2.836	0.556	1.306	1.016	0.778
47	Landmarks Preservation Commission	74	4.182	4.182	1.000	1.070	1.070	1.000
48	Law Department	1591	2.442	2.442	1.000	0.625	0.625	1.000
49	Mayoralty	1321	2.505	2.505	1.000	0.641	0.641	1.000
50	Municipal Water Fin Authority	11	7.507	3.336	0.444	1.921	1.342	0.699
51	New York City Council	693	2.752	2.752	1.000	0.704	0.704	1.000
52	New York City Fire Pension Fund	49	4.625	3.597	0.778	1.183	1.069	0.903
53	New York City Police Pension Fund	149	3.597	3.597	1.000	0.920	0.920	1.000
54	New York City Tax Commission	53	4.534	3.526	0.778	1.160	1.048	0.903
55	NYC Civil Service Commission	15	6.647	4.431	0.667	1.701	1.437	0.845
56	NYC Emergency Management	224	3.326	2.587	0.778	0.851	0.769	0.903

57	NYC Employees Retirement System	502	2.895	2.895	1.000	0.741	0.741	1.000
58	NYC Health And Hospitals	40433	1.697	1.697	1.000	0.434	0.434	1.000
59	NYC Housing Authority	12045	1.916	1.916	1.000	0.490	0.490	1.000
60	Office Of Administrative Trials And Hearings	696	2.750	2.750	1.000	0.704	0.704	1.000
61	Office Of Collective Bargaining	16	6.492	4.328	0.667	1.661	1.404	0.845
62	Office Of Payroll Administration	143	3.627	3.224	0.889	0.928	0.885	0.954
63	Office Of Technology And Innovation	1590	2.442	2.442	1.000	0.625	0.625	1.000
64	Office Of The Actuary	46	4.701	3.657	0.778	1.203	1.086	0.903
65	Office Of The City Clerk	65	4.312	3.354	0.778	1.103	0.996	0.903
66	Office Of The Comptroller	721	2.735	2.735	1.000	0.700	0.700	1.000
67	Office Of The Public Advocate	75	4.169	4.169	1.000	1.067	1.067	1.000
68	Offices Of The Public Administrators	48	4.650	3.100	0.667	1.190	1.005	0.845
69	Police Department	54253	1.651	1.651	1.000	0.422	0.422	1.000
70	Taxi & Limousine Commission	540	2.861	2.861	1.000	0.732	0.732	1.000
71	Teachers Retirement System	346	3.079	2.737	0.889	0.788	0.752	0.954

Table 6. Descriptive statistics for G and G_{LN} income diversity scores for FY 2022

	Indices			
Statistic	G	G_G	G_{LN}	G_{LNG}
Minimum	1.519	0.444	0.389	0.699
Maximum	4.829	1.000	1.566	1.000
Range	3.311	0.556	1.178	0.301
Median	2.836	1.000	0.747	1.000
Mean	2.959	0.925	0.810	0.966
95% CI Mean Upper Bound	3.146	0.955	0.872	0.980
95% CI Mean Lower Bound	2.771	0.894	0.747	0.951
Standard Deviation	0.793	0.128	0.264	0.062
Skewness	0.357	-1.754	0.728	-2.132
Std. Error of Skewness	0.285	0.285	0.285	0.285
Kurtosis	-0.729	2.552	0.083	4.875
Std. Error of Kurtosis	0.563	0.563	0.563	0.563
Coefficient of variation	0.268	0.139	0.326	0.064
Shapiro-Wilk	0.966	0.649	0.948	0.626
P-value of Shapiro-Wilk	0.054	0.000	0.005	0.000
N	71	71	71	71



Based on the CV measures obtained for each set of income variation scores, the distribution of unstandardized G_{LN} scores has the largest amount of measurement variability ($CV_{GLN} = 0.326$) and suggests that the index has the highest degree of discriminatory power to detect subtle differences in the level of income variation amongst NYC municipal departments. With a CV score of 0.27 ($CV_G = 0.268$), the distribution of unstandardized G scores has the second highest amount of measurement variability. The distribution of GLNG scores has the lowest CV score of 0.06 ($CV_{GLN} = 0.064$), indicating that the G_{LN} index possesses the lowest amount of discriminatory power to detect subtle differences in the level of income variation amongst NYC departments. When the CV and standard deviation scores are considered concomitantly, they indicate that that the G_{LNG} scores are clustered more closely around the mean in comparison to the income variation scores obtained by the G index.

B. Pearson Correlation Analysis

As stated in the methodology section, Pearson correlation analysis was undertaken to assess how well the unstandardized and generalized G and G_{LN} scores are interrelated. Table 7 summarizes the findings of the Pearson correlation analysis. The findings indicate that the G and G_G scores have a significant low negative statistical relationship ($r = -0.406$, $p < 0.001$). A significant low negative statistical relationship also exists amongst the G and G_{LNG} scores ($r = -0.386$, $p < 0.001$). These low interrelations amongst the income variation scores is due to G producing a normally distributed set of unstandardized scores while G_G and G_{LNG} produced significantly negatively skewed and heavy-tailed distributions of generalized scores, respectively. A near perfect positive statistical relationship exists amongst the G and G_{LN} diversity scores ($r = 0.940$, $p < 0.001$) due to producing scores that are similar and that vary in the same direction. For similar reasons, a near perfect positive relationship exists among the G_G and G_{LNG} diversity scores.

C. PCA and Parallel Analyses

The findings of the PCA with oblique oblimin rotation and the parallel analyses are summarized in Table 8. The construct validity assessments indicate that the indices measure the same dimension of vertical income variation. As shown in Panel A, the initial unrotated solution identified one component with an eigenvalue of 3.05 that accounts for 76% of the variance in the data. When the income variation scores were rotated with oblique oblimin, one component was identified and has a sum of squares (SS) loading of 3.05 (see Table 8, Panel B). Additionally, the component accounts for 76% of the variance in the data.

G_{LN} has a component loading of -0.938 with a uniqueness score of 0.12, indicating that 12% of the variance is attributable solely to the G_{LN} index. G_G has an SS loading of 0.893 with a uniqueness score of 0.203, indicating that 20% of the variance is attributable solely to the G_G index. G_{LNG} has a slightly lower SS loading of 0.884 with a uniqueness score of 0.219. While G obtained an SS loading of -0.772, the index has the highest uniqueness score of 0.404, indicating that 40% of the variance is attributable solely to the index. Briefly, the parallel analysis also identified one component. Accordingly, the parallel analysis indicates that the G and G_{LN} indices assess the same dimension of income variation based on the salary-related data reported by NYC departments for FY 2022 (as highlighted in table 8 below).

D. Measurement Reliability

Because numerous NYC departments reported imprecise salary-related data for their labor force, the unstandardized and generalized G and G_{LN} income variation scores were assessed for measurement reliability. The findings of the measurement reliability assessments are presented in Table 9. In Panel A, the assessments reveal that the G and G_{LN} indices produce reliable unstandardized measures of income variation despite the imprecision of the salary-related data. A Cronbach's α coefficient of 0.969 with a measurement error (ME) score of 0.06 (ME = 1 – 0.9692 = 0.061) was obtained for the unstandardized G and G_{LN} scores. When the unstandardized G and G_{LN} scores were assessed with the greatest lower bound method, a coefficient of 0.934 with an ME score of 0.128 was obtained. In addition, an average inter-item correlation coefficient of 0.940 with an ME score of 0.116 was obtained for the unstandardized scores.

Based on the Cronbach's α coefficient, a standard error of measurement (SEM) score of 0.14 ($SEM_G = \sigma \sqrt{(1\text{-}r)} = 0.793 \sqrt{(1\text{-}0.969)} = 0.140$) was obtained for the unstandardized G scores (see Table 9, Panel A). The SEMG scores indicates that the G scores would deviate by 0.14 standard deviations if NYC departments were measured repeatedly with the index. A SEM score of 0.05 (SEMGLN = 0.046) was obtained for the unstandardized G_{LN} scores. If the G_{LN} index were applied to the pay dispersion data reported by NYC departments repeatedly, the logarithm-based scores would deviate by 0.05 standard deviations. The difference between the SEMG and SEMGLN scores is due to the difference in the standard deviation scores obtained for the unstandardized G ($\sigma G = 0.793$) and G_{LN} ($\sigma G_{LN} = 0.264$) vertical pay dispersion scores (see table 9 below).

Due to lower measurement variability amongst the distribution of generalized G_G and G_{LNG} income variation scores, higher measurement reliability coefficients were obtained (see Table 9, Panel B). A Cronbach's α coefficient of 0.998 with an ME score of 0.004 was obtained for the G_G and G_{LNG} scores. A smaller greater, lower bound coefficient of 0.966 with an ME score of 0.008 was obtained for the generalized scores.

Table 7. Pearson correlation analysis of G and G_{LN} income diversity scores for FY 2022

	Indices			
Indices	G	G_G	G_{LN}	G_{LNG}
G	—			
G_G	-0.406 *	—		
G_{LN}	0.940 *	-0.683 *	—	
G_{LNG}	-0.386 *	0.996 *	-0.670 *	—

* $p < 0.001$

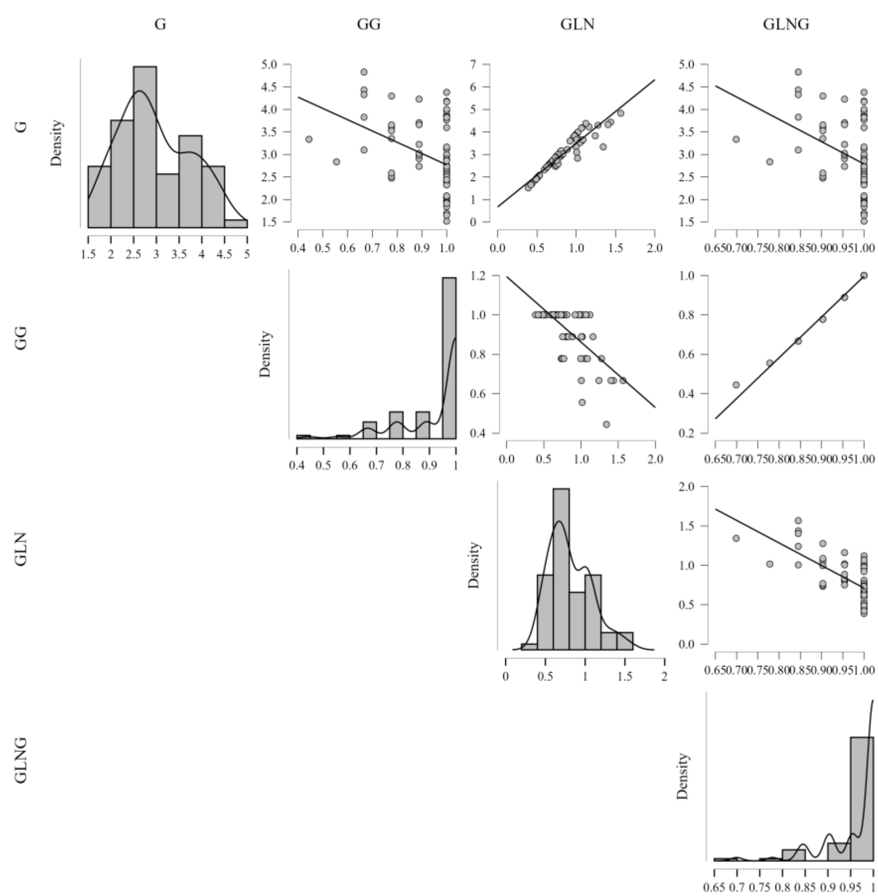


Table 8. PCA for G and G_{LN} income diversity scores for FY 2022

A. Initial unrotated solution

Component	Eigenvalue	% of Variance	Cumulative %
1	3.054	76.36	76.4
2	0.938	23.45	99.8
3	0.006	0.14	99.9
4	0.002	0.05	100

B. Oblique oblimin rotation

Component	Sums of Squares Loadings	% of Variance	Cumulative %
1	3.05	76.4	76.4

	Component 1	
Indices	Component loadings	Uniqueness
G_{LN}	-0.938	0.120
G_G	0.893	0.203
G_{LNG}	0.884	0.219
G	-0.772	0.404

C. Parallel PCA analysis

	Real data component eigenvalues	Simulated data mean eigenvalues
Component 1*	3.054	1.313
Component 2	0.938	1.078
Component 3	0.006	0.875
Component 4	0.002	0.734

* Component should be retained.

Table 9. Measurement reliability assessment of G and G_{LN} income diversity scores for FY 2022

A. Unidimensional reliability assessment of G and G_{LN} scores

Estimate	Cronbach's α	Measurent Error	Greatest Lower Bound	Measurent Error	Average interitem correlation	Measurent Error	Cronbach SEM_G	Cronbach SEM_{GLN}
Point estimate	0.969	0.061	0.934	0.128	0.940	0.116	0.140	0.046
95% CI lower bound	0.951	0.096	0.890	0.208	0.900	0.190		
95% CI upper bound	0.981	0.038	0.965	0.069	0.969	0.061		

B. Unidimensional reliability assessment of G_S and G_{LNS} scores

Estimate	Cronbach's α	Measurent Error	Greatest Lower Bound	Measurent Error	Average interitem correlation	Measurent Error	Chronbach SEM_{GG}	Cronbach SEM_{GLNG}
Point estimate	0.998	0.004	0.996	0.008	0.996	0.008	0.006	0.003
95% CI lower bound	0.996	0.008	0.994	0.012	0.994	0.012		
95% CI upper bound	0.999	0.002	0.999	0.002	0.999	0.002		

As noted previously, a greater lower bound coefficient of 0.934 with a ME score of 0.128 was obtained for the G and G_{LN} scores. Lastly, an average inter-item correlation coefficient of 0.966 with an ME score of 0.008 was obtained for the G_G and G_{LNG} scores. Because the distributions of the G_G and G_{LNG} scores have less measurement variability than their unstandardized counterparts, larger reliability coefficients were obtained for the generalized scores.

Concomitantly, the SEM scores obtained for the G_G and G_{GLN} scores are smaller than those obtained for the G and G_{LN} scores (see Table 9, Panel B). The differences are due to the differences in measurement variability amongst the distributions of unstandardized and standardized G and G_{LN} scores. For the G_G scores, an SEMG score of 0.006 (SEMG = 0.006) was obtained, indicating that G_G scores would deviate by 0.006 standard deviations if generalized G scores were obtained repeatedly from NYC departments. Due to the clustering of G_{LNG} around the mean, an SEM score of 0.003 (SEMGLNG = 0.003) was obtained for the index. When compared to the distribution of G_G scores, G_{LNG} has a smaller standard deviation score which contributes to a smaller SEM score.

5. Discussions

Due to the poor quality of the human capital- and labor-based data reported by NYC departments for FY 2022, accurate, compatible, and reliable Shannon, Simpson, and Wilcox variation scores for vertical pay dispersion could not be obtained. In the case of the Shannon index, the lack of precise frequency and percentage information for each salary category prohibited the application of the index to each NYC department. Specifically, unstandardized and generalized H scores for vertical income variation could not be obtained due to a lack of data specificity or due to missing information for one or more salary categories.

A. *Applying the Simpson index*

In the case of the Simpson index, the lack of specificity with respect to the number of employees in each salary category prohibited the application of the index to each department. When the index was applied to the percentage associated with each salary category, the accuracy and reliability of the unstandardized and generalized vertical pay dispersion scores was questionable due to departments under- or overreporting the percentages. The total percentage for the salary categories exceeded 100% for some NYC departments. For other departments, the total percentage for the salary categories was under 100%. In short, the computational and rounding errors associated with the salary-related data prohibited obtaining unbiased Simpson scores for vertical income variation for each NYC department.

B. *Applying the Wilcox mode-based index*

Computational or rounding errors associated with the salary-related data also prohibited obtaining compatible and reliable Wilcox heterogeneity scores for annual income for each NYC department. As a result of the computational or rounding errors, the salary category with the largest frequency or percentage was undeterminable for numerous departments and restricted the applicability of the index. In other cases, the imprecision of the percentages associated with the salary categories contributed to the index under- or overreporting the level of vertical income variation due to the mode being inaccurate. The imperfect or imprecise data compromised the accuracy, compatibility, and reliability of the Wilcox scores of vertical income variation.

C. Applying the Guajardo count- and logarithm-based indices

The count- and logarithm-based Guajardo indices were applied to the salary-related data as alternatives to the Shannon, Simpson, and Wilcox indices. Unlike the Shannon, Simpson, and Wilcox indices that require precise frequency or percentage data for each category of a human capital or labor characteristic to obtain heterogeneity scores, the Guajardo indices assign a value of 1 to the categories with at least one employee and sums the scores. As such, heterogeneity scores obtained by the Guajardo indices are not influenced by the accuracy or inaccuracy of the human capital or labor force data. Accordingly, the unstandardized G and G_{LN} scores for income heterogeneity are positively correlated. Similarly, the generalized G_G and G_{LNG} income variation scores are positively correlated. Additionally, based on the PCA and parallel analyses, the G and G_{LN} indices assess the same dimension of income variation. Despite the imprecision of the salary-related data reported by NYC departments, the Guajardo indices produced income variation scores with high levels of measurement reliability.

Although the Guajardo indices produced reliable income variation scores, the count- and logarithm-based indices differed with respect to measurement variability and discriminatory power. The G_{LN} index produced a distribution of unstandardized diversity scores with the largest level of measurement variability, indicating that the index has a greater ability to detect subtle differences in the level of income variation amongst NYC departments. By contrast, the G index has a lower ability to detect subtle differences in income variation due to its distribution of scores having a lower amount of measurement variability. Based on the findings, the G_{LNG} index has the lowest ability to detect subtle changes in the level of income variation

Although the G_G and G_{LNG} indices produced reliable income variation scores, the use of the generalized G_G and GLNG indices have several drawbacks (or disadvantages). First, the indices produced distributions of generalized scores that varied negatively with their respective unstandardized scores. The negative statistical association amongst the unstandardized and generalized G and G_{LN} scores was obtained because high unstandardized G and G_{LN} scores were reduced to a generalized score of 1 when the G_G and G_{LNG} formulas were applied to their respective unstandardized scores. Second, the indices produced distributions of generalized scores that were clustered more closely around the mean due to the reduction in measurement variability. Specifically, converting the unstandardized G and G_{LN} scores to generalized scores compressed the distributions by reducing the range between the highest and lowest unstandardized scores. Concomitantly, the conversion of the unstandardized G and G_{LN} scores reduced the measurement variability of the G_G and G_{LN} distributions as high unstandardized G and G_{LN} scores were reduced to a generalized score of 1. Third, the indices produced distributions of generalized scores that were negatively skewed with positive kurtosis and that violated the assumption of normality. This is due to the compression of the distributions of G and G_{LN} scores when generalized scores were obtained, due to the reduction of high unstandardized G and G_{LN} scores to generalized scores of 1, and due to the reduction of measurement variability as unstandardized G and G_{LN} scores were converted to generalized scores. By contrast, the distribution of unstandardized G scores is normally distributed with slight positive skewness and negative kurtosis. Despite violating the assumption of normality, the distribution of unstandardized G_{LN} scores is positively skewed and has a low level of positive kurtosis.

Unlike the Shannon and Simpson indices which produce accurate measures of equitability, the G and G_{LN} indices do not do so. When generalized Shannon and Simpson scores of 1 are obtained, the score indicates that employees are distributed equally between the annual income categories. By contrast, a generalized G or G_{LN} score of 1 indicates that a NYC department has at least one employee in each annual income category. Due to ignoring the frequency or percentage associated with each annual income category, the G and G_{LN} indices produce a crude pseudo-measure of equitability where a NYC department has at least one employee in each income category.

D. Theoretical implications

Despite the measurement drawbacks and limitations of the count- and logarithm-based G and G_{LN} indices, the application of the indices to human capital and labor force data has theoretical implications. If the G, G_{LN}, Shannon, Simpson, and Wilcox indices are applied to the same human capital or labor force data, the G and G_{LN} indices are likely to produce significantly different statistical results when compared to the Shannon, Simpson, and Wilcox indices. Specifically, the G and G_{LN} indices are likely to detect significant statistical relationships amongst organizational-based predictors and the unstandardized scores of variation when the Shannon and Simpson indices fail to do so. Unlike the G and G_{LN} indices, the Shannon and Simpson indices produce distributions of unstandardized variation scores that are restricted by the number of categories created for human capital or labor force characteristics. In the case of the annual income categories, the Shannon index has a minimum unstandardized score of 0.0 and a maximum unstandardized score of 2.3 (HM = lnK = ln10 = 2.30; see Table 2). The Simpson index has a minimum unstandardized score of 0.0 and a maximum unstandardized score of 0.9 (SM (K-1)/K= = (10 - 1)/10 = 0.90; see Table 2). By contrast, the G index has a minimum unstandardized score of 0 and produces a maximum unstandardized score of 7.51 (see Table 2 and 5). However, the G_{LN} index has a minimum unstandardized score of 0 and produces a maximum unstandardized score of 1.92 (see Table 2 and 5). Because the G and G_{LN} indices produce distributions of unstandardized scores with greater levels of measurement variability, multivariate statistical analyses are more likely to detect more significant statistical findings associated with the G and G_{LN} scores than with the Shannon and Simpson scores.

The application of the Wilcox mode-based, G, and G_{LN} indices to the same annual income data are likely to produce similar statistical findings due to the indices producing distributions of unstandardized variation scores with similar levels of measurement variation. Based on the data collected for the annual income categories used by NYC departments, the Wilcox mode-based index produces a minimum unstandardized score of 0 and a maximum unstandardized score of 9 (WMM = K – 1 = 10 – 1 = 9; see Table 2). In this study, the largest unstandardized score obtained by the G index was 7.51 (see Table 5). Regrettably, the imprecise data reported by NYC departments prohibited the obtainment of accurate WM scores of vertical pay dispersion.

Although the G, G_{LN}, Shannon, Simpson, and Wilcox mode-based indices produced generalized scores ranging from 0 to 1, the indices produce distributions with different levels of measurement variation which affect the statistical relationships between organizational-based predictors and the scores of pay dispersion. When compared to other indices of variation, the Simpson index generally produces a distribution of generalized scores with the least amount of measurement variation (Guajardo, 2023a, 2023b, 2023c, and 2024b). The loss of measurement variation that occurs when converting unstandardized Simpson scores to generalized scores often produces nonsignificant statistical findings amongst organizational-based predictors and the variation scores (Guajardo, 2023b and 2023c). Additionally, the conversion of unstandardized Simpson scores to generalized scores reduces the explanatory power of regression-based statistical models (Guajardo, 2023b and 2023c). The conversion of unstandardized Shannon scores to generalized scores also reduces the level of measurement variability in the distribution of scores as well as the explanatory power of regression-based statistical models (Guajardo, 2023a). While the conversion of unstandardized G and G_{LN} scores to generalized scores reduces the level of measurement variation of the respective distributions, the reduction in the level of explanatory power is not as large as the loss of explanatory power associated with the Shannon and Simpson indices. More significant statistical findings are likely to be detected with the use of generalized G and G_{LN} scores than with generalized Shannon and Simpson scores.

As discussed previously, extant research shows that the level of pay dispersion amongst employees significantly affects organizations in terms of attaining performance outcomes, enhancing fiscal performance, and maintaining (or reducing) the level of human capital attrition (or turnover) that occurs in a workforce. Due to producing distributions of unstandardized and standardized scores of variation with greater measurement variability in comparison to other diversity indices, the use of the G and G_{LN} indices to assess horizontal or vertical pay dispersion within organizations has the potential to detect significant statistical relationships that may not be detected with the use of the Shannon, Simpson, or Wilcox mode-based indices (see Figure 1).

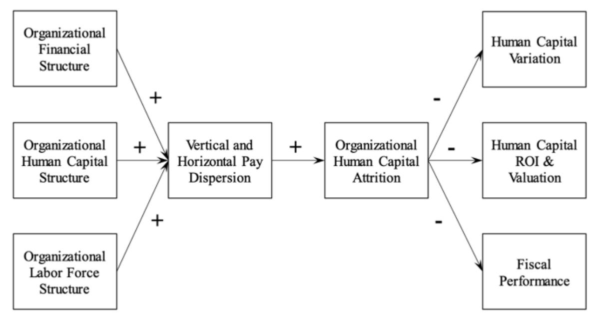


Fig. 1 Theoretical formative structural equation model for model performance

When the G and G_{LN} indices are used to measure pay dispersion, the unstandardized and standardized scores should have significant positive statistical relationships with workforce attrition where organizations with greater levels of pay dispersion experience greater levels of human capital turnover. As workforce turnover increases, organizations should experience a loss in human capital variation in terms of demographic (or social) and work-related characteristics such as years of service. Increased workforce turnover should also decrease human capital productivity and return on investment (ROI) in organizations where the level of profit per employees decreases for every dollar invested in human capital (Fitz-enz, 2009; Fitzenz and Davison, 2002). In addition, fiscal performance such as net profit margin should decrease as workforce turnover increases in organizations with higher levels of pay dispersion. Briefly, pay dispersion should have significant negative indirect effects on human capital variation, human capital valuation, and on fiscal performance.

E. Practical implications

When organizations report imprecise categorical human capital or labor force data, the following criteria should guide the decision to use the G and G_{LN} indices to assess and measure workforce-related variation:

The total number of individuals in an assemblage is equal to or greater than the total number of attributes ($N \geqslant K$) created for a workforce-related characteristic. When

K exceeds N ($K > N$ or $N < K$), an assemblage of individuals is prohibited from obtaining perfect heterogeneity (or equitability) because the number of attributes exceeds the total number of positions so that one or more of the attributes will lack at least one individual in the category. When this condition is not satisfied, a count-based index will not assess the level of variation in an organization accurately.

The ratio of K to N is equal or greater than 1 ($\bar{k} \geqslant N/K$) so that a state of perfect heterogeneity with at least one individual in each attribute is attainable. When this condition is not satisfied, $N < K$ because the number of attributes created for a workforce-related characteristic exceeds the total number of individuals in an assemblage.

Under the condition of perfect heterogeneity (or equitability), $\Sigma k - 1$ is one unit less than the total number of attributes (K) created for a workforce-related characteristic ($\Sigma k - 1 < K$). Satisfying this condition ensures that a minimum value of 0 is obtained when perfect homogeneity exists in an assemblage.

Under the condition of perfect homogeneity, a count-based index of diversity produces a score of 0, indicating the absolute absence of heterogeneity.

When unstandardized count-and logarithm-based scores of variation are standardized, the distribution of standardized scores ranges from 0 to 1 to facilitate the comparison of variation scores obtained for the same distribution by two or more indices of variation (Wilcox, 1967).

Count- and logarithm-based indices produce compatible, valid, and reliable variation scores for a workforce characteristic when the measurement criteria are satisfied.

The decision to use the G and G_{LN} indices should be based on whether the unstandardized and standardized scores of variations provide sufficient information to make informed decisions about addressing human capital- and workforce-related disparity issues in the organization. While unstandardized G and G_{LN} scores of variations are valid and reliable when imperfect categorical human capital or workforce data are reported, the scores do not utilize all of data as thoroughly as the Shannon or Simpson indices. Unlike the Shannon and Simpson indices of variation, the G and G_{LN} indices ignore the frequencies and percentages reported for each category created for a categorical human capital or labor force characteristic. Utilizing generalized G and G_{LN} scores for making decision about addressing human capital- and workforce-related disparity issues also presents challenges. Specifically, generalized G and G_{LN} scores are crude pseudo-measures of equitability that provide limited information about the distribution of employees across a human capital or labor force characteristic. Despite the drawbacks and limitations of the G and G_{LN} indices, they are appropriate and useful for assessing organizational variation when the quality of human capital or labor force data is compromised and when the application of frequency-based indices of disparity and variation is infeasible, inappropriate, or questionable.

The use of the G and G_{LN} indices also presents challenges when comparing human capital or labor force disparity between organizations. When significant differences in the quality of human capital or labor force data reported by peer organizations exist, the use of the G and G_{LN} indices may over report the level of variation for several organizations. As discussed previously, generalized G and G_{LN} scores are concentrated at the higher values of a distribution and overstate the level of equitability across a categorical human capital or labor force characteristic.

6. Conclusion And Future Work

This article addressed how imperfect or imprecise human capital- and labor-based data adversely affect the ability to apply logarithm-, mode-, and probability-based indices of variation and to obtain accurate measures of heterogeneity when addressing organizational (or workforce) disparity. In addressing the issue, this article presented how count-based diversity indices obtain reliable measures of heterogeneity (or variation) when organizations report imperfect or imprecise human capital- and labor-based data. To this end, count-based indices of variation are useful and serve as viable alternative methods of obtaining measures of heterogeneity when data specificity is lacking or when human capital- or labor-based data reported by organizations are inconsistent.

This article contributes to the assessment and measurement of organizational heterogeneity by providing a method (or technique) for obtaining unstandardized and generalized measures of variation based on imperfect data. Specifically, this article provides a method for addressing data analytical challenges posed by imprecise categorical human capital or labor force data when measuring organizational variation. As illustrated in this article, the G and G_{LN} indices obtain dependable and valid measures of variation when faulty human capital or labor force data prohibit the application of the coefficient of variation, the Gini coefficient, or the Shannon, Simpson, or Wilcox mode-based indices.

The application of the count- and logarithm-based G and G_{LN} indices has the potential to detect significant statistical relationships amongst organizational-based predictors and organizational variation that may not be detectable by other measures of variation such as the Shannon and Simpson indices. Because the Shannon and Simpson indices produce distributions of scores of variation that are compressed by the number of categories created for a categorical human capital or labor force characteristic, the lack of measurement variability produces nonsignificant statistical findings (Guajardo, 2023b and 2023c). Stated differently, the moderate level of measurement variability diminishes the strength of the statistical relationships amongst the organizational-based predictors and the unstandardized and generalized Shannon and Simpson scores. By contrast, the level of measurement variability is greater in the distributions of the unstandardized and generalized G and G_{LN} scores, thereby increasing the likelihood of detecting more significant statistical relationships. When a formative structural equation model is used to assess the statistical relationships between exogenous composites of human capital or labor force disparity or variation and endogenous composites of organizational performance (see Figure 1), significant indirect effects are likely to be detected amongst unstandardized and generalized G and G_{LN} scores and endogenous composites of organizational performance.

Future research should apply count-based indices of variation to other organizational settings and to other human capital and labor data. By doing so, a greater understanding of the applicability and robustness of count-based indices to obtain reliable measures of variation would be obtained. Future research should also examine how the use of count-based indices enhances human capital or labor analytics when accurate and precise data are not readily available. Under such conditions, count-based indices of variation may provide the best measures of human capital and labor force heterogeneity.

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APPENDIX A: Annual compensation data for NYC municipal departments for FY 2022

			Annual Compensation										
Case	NYC Department	Headcount	<40k	$40k to 50k	$50k to 60k	$60k to 70k	$70k to 80k	$80k to 90k	$90k to 100k	$100k to 110k	$110k to 120k	$120k+	Σk
1	Administration For Children's Services	6857	171	617	961	2653	417	930	402	280	159	267	10
2	Board Of Correction	23		1	1	5	1			7	1	6	7
3	Board Of Election	897	304	191	208	70	29	22	21	11	8	33	10
4	Borough President-Bronx	92	1	12	9	17	15	11	9	5	1	11	10
5	Borough President-Brooklyn	103	8	8	14	12	15	7	15	8	5	11	10
6	Borough President-Manhattan	90	1	8	10	25	9	7	10	7	1	11	10
7	Borough President-Queens	109	16	1	14	22	15	5	10	1	10	10	10
8	Borough President-Staten Is	44		1	7	10	8	6	1	1	1	5	9
9	Business Integrity Commission	75		16	9	20	1	1	1	1	1	14	9
10	Campaign Finance Board	119	1	1	16	11	9	18	8	12	11	27	10
11	City Commission On Human Rights	111	5	1	12	33	11	14	13	1	1	16	10
12	Civilian Complaint Review Board	245		59	24	53	1	19	1	25	19	40	9
13	Conflicts Of Interest Board	26		1	1	1	1	1	1		1	8	8
14	Department For The Aging	322	1	17	33	71	51	53	24	14	15	43	10
15	Department Of Citywide Admin Svcs	2113	496	109	246	214	183	143	153	117	76	376	10
16	Department Of Buildings	1605	61	123	93	501	245	207	92	73	69	141	10
17	Department Of City Planning	287		<5	20	59	61	39	41	11	12	42	8
18	Department Of Consumer And Worker Protection	422	12	106	64	69	40	41	28	11	17	34	10
19	Department Of Correction	8996	37	472	407	1223	167	122	5597	82	590	299	10
20	Department Of Cultural Affairs	79	1		16	9	13	7	1	5	6	18	9
21	Department Of Design & Construction	1151	1	20	80	167	195	146	140	112	63	225	10
22	Department Of Education	140383	21805	17004	1857	7458	13709	14270	13083	20865	7783	22549	10
23	Department Of Environment Protection	5733	233	454	428	970	561	415	1302	372	206	792	10
24	Department Of Finance	1823	27	219	209	290	219	181	176	174	83	245	10
25	Department Of Health/Mental Hygiene	6468	210	746	711	1843	674	733	500	333	184	534	10
26	Department Of Homeless Services	1974	344	269	395	457	126	131	66	48	24	114	10
27	Department Of Investigation	295	1	9	73	33	45	29	27	20	14	44	10
28	Department Of Parks & Recreation	6805	1427	1656	1199	580	724	393	326	123	173	204	10
29	Department Of Probation	1009	38	150	347	146	199	42	33	18	14	22	10
30	Department Of Records & Info Service	61	8	8	10	16	1	1	1	1	1	5	10
31	Department Of Sanitation	9748	128	1637	555	376	126	4673	923	110	739	481	10
32	Department Of Small Business Services	262			11	65	54	39	26	17	1	46	8
33	Department Of Transportation	5779	124	975	1014	670	562	367	777	464	248	578	10
34	Department Of Youth & Community Development	506	24	1	35	129	75	65	41	44	31	59	10
35	District Attorney - Bronx County	983	86	148	129	93	148	131	5	35	28	180	10
36	District Attorney - Kings County	1163	77	244	93	84	246	70	74	61	29	185	10
37	District Attorney - Manhattan	1532	39	333	174	116	185	137	108	76	57	307	10
38	District Attorney - Queens County	811	103	115	54	28	156	90	40	46	14	165	10
39	District Attorney - Richmond County	214		19	53	25	32	31	1	7	11	32	9
40	District Attorney - Special Narcotics	198		1	21	12	28	29	11	18	13	63	9
41	Equal Employment Practices Commission	12			1	1	1	1	1		1	1	7
42	Financial Information Services Agency	406	1	9	16	13	20	31	23	27	50	214	10
43	Fire Department	17712	492	2345	2095	1546	883	561	6887	410	1231	1262	10
44	Housing Preservation & Development	2323	101	229	251	639	345	218	138	127	116	159	10
45	Human Resources Administration	11364	354	5085	1986	1339	645	589	484	286	233	363	10
46	Independent Budget Office	34				1	7	7	1	1		12	6
47	Landmarks Preservation Commission	74	1	1	5	21	18	8	1	1	1	8	10
48	Law Department	1591	15	435	143	75	199	47	112	84	68	413	10
49	Mayoralty	1321	22	49	83	171	156	143	119	107	71	399	10
50	Municipal Water Fin Authority	11				1	1		1		1	5	5
51	New York City Council	693	65	38	86	109	82	53	41	38	22	159	10
52	New York City Fire Pension Fund	49		9	1	9	7	5	1	5		10	8
53	New York City Police Pension Fund	149	12	25	19	21	11	17	1	5	10	26	10
54	New York City Tax Commission	53	1			1	1	9	1	8	7	14	8
55	NYC Civil Service Commission	15		1		1	1	1		1	1	5	7
56	NYC Emergency Management	224			1	44	57	16	31	25	10	38	8
57	NYC Employees Retirement System	502	24	88	136	55	37	30	26	24	14	68	10
58	NYC Health And Hospitals	40433	3010	11478	4260	3391	2437	8328	2470	954	1117	2988	10
59	NYC Housing Authority	12045	2025	3039	673	2328	937	736	997	461	220	629	10
60	Office Of Administrative Trials And Hearings	696	70	50	24	45	24	20	54	315	6	88	10
61	Office Of Collective Bargaining	16			1	1	1	1	1		1	9	7
62	Office Of Payroll Administration	143		8	12	14	19	26	16	11	1	34	9
63	Office Of Technology And Innovation	1590	78	199	103	74	124	128	134	107	149	494	10
64	Office Of The Actuary	46			7	8	1	5	1	1	1	16	8
65	Office Of The City Clerk	65	1	32	8	8		1	1		1	6	8
66	Office Of The Comptroller	721	10	35	105	107	96	76	72	32	42	146	10
67	Office Of The Public Advocate	75	18	1	19	8	1	1	8	6	1	5	10
68	Offices Of The Public Administrators	48	1	21	1	5	1	1				13	7
69	Police Department	54253	4601	12337	6441	1070	422	14682	1878	5063	3606	4153	10
70	Taxi & Limousine Commission	540	24	146	137	94	45	22	20	9	8	35	10
71	Teachers Retirement System	346		25	75	42	36	29	28	21	11	79	9

Note: <5 was replaced with 1 to obtain an accurate count of the salary categories with at least one employee.