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Beyond mean pay gaps: Decomposing earnings inequality among registered nurses

David Kalist
Shippesnburg University

Abstract

Using the 2018 and 2022 U.S. National Sample Survey of Registered Nurses (NSSRN), I use Theil index decompositions to examine the structure of RN earnings inequality. More than 96% of earnings inequality occurs within demographic groups rather than between them. Differences in mean earnings by sex and race/ethnicity explain little of total inequality, while education and geography account for somewhat larger between-group shares. Results using hourly wages are similar. The findings indicate substantial earnings heterogeneity among nurses even within narrowly defined demographic categories.

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Contact: David Kalist - dekali@ship.edu.
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1. Introduction

Using the 2018 and 2022 U.S. National Sample Survey of Registered Nurses (NSSRN), I decompose earnings inequality among U.S. registered nurses (RNs) into within-group and between-group components by sex, race/ethnicity, race/ethnicity-by-sex interactions, education, employment setting, and geography using the Theil index (GE(1)). Registered nursing is a highly skilled, licensed profession with almost 3.4 million employed workers and a median annual salary of $93,600 in 2024, making it one of the largest occupations in the U.S. healthcare workforce and an important setting for studying earnings inequality.[1] I find that more than 96% of RN earnings inequality occurs within demographic groups rather than between them.

The Theil index is useful because it permits additive decomposition of total inequality into inequality arising within groups and inequality arising between groups. As a result, the decomposition distinguishes whether observed earnings inequality primarily reflects differences in average earnings across groups or dispersion among individuals within the same group.

Differences in mean earnings by sex and race/ethnicity explain only a small share of total RN earnings inequality. Education and geography account for somewhat larger between-group components, though within-group dispersion remains dominant across all decompositions. Results using hourly wages are qualitatively similar.

These findings complement the existing literature on demographic pay gaps in nursing by showing that overall earnings inequality and mean group differences are distinct phenomena. While demographic mean gaps exist, most RN earnings inequality reflects substantial heterogeneity among nurses within narrowly defined demographic groups.

2. Background

Research on RN earnings has focused primarily on mean pay differences across demographic groups, especially differences between male and female nurses (Kalist, 2002; Jones and Gates, 2004; Muench et al., 2015; Dill and Frogner, 2023; Estrada et al., 2026). Wilson et al. (2018), for example, estimate that male nurses earn roughly 10% more than female nurses. Existing research therefore emphasizes differences in average earnings across groups rather than the overall structure of earnings inequality within the nursing profession.

This paper complements the existing literature by decomposing RN earnings inequality into within-group and between-group components by sex, race/ethnicity, race/ethnicity-by-sex interactions, education, employment setting, and geography using the Theil index (GE(1)). The analysis examines whether observed earnings inequality primarily reflects differences in mean earnings across groups or dispersion among nurses within the same groups.

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[1] Bureau of Labor Statistics, U.S. Department of Labor, Occupational Outlook Handbook, Registered Nurses, at https://www.bls.gov/ooh/healthcare/registered-nurses.htm

Registered nursing is one of the largest female-dominated occupations in the United States, with women comprising roughly 87% of employed RNs. [2] As a result, studying the structure of earnings inequality within nursing has implications for assessing labor market equity and for understanding compensation differences within a large healthcare occupation.

3. Data, Variables, and Methods

I use data from the 2018 and 2022 National Sample Survey of Registered Nurses (NSSRN), a nationally representative survey of registered nurses conducted by the U.S. Department of Health and Human Services. The analytic sample is restricted to employed RNs with positive earnings. The 2022 sample contains 40,992 observations, while the 2018 sample contains 43,764 observations. Because the 2022 survey coincided with the COVID-19 pandemic—an event that may have affected earnings patterns and labor market dynamics—results from the 2018 NSSRN are used to assess the sensitivity of the findings.

The primary outcome variable is annual earnings. Supplemental analyses examine hourly wages, defined as annual earnings divided by annual hours worked, restricting the sample to nurses reporting at least 1,000 annual hours. The NSSRN collects earnings information for the prior calendar year; therefore, the 2022 survey reflects registered nurses' earnings in 2021, and the 2018 survey reflects earnings in 2017.

I decompose earnings inequality by sex, race/ethnicity, race/ethnicity-by-sex interactions, education (highest nursing degree), employment setting (hospital versus non-hospital), and state of employment.[3] There are five educational categories: diploma; associate degree (including LPN-to-RN programs); bachelor's degree; master's degree (or post-master's certificate); and doctoral preparation. In the 2018 survey, there are eight race/ethnicity categories: Hispanic, white non-Hispanic, black non-Hispanic, Asian non-Hispanic, American Indian non-Hispanic, Pacific Islander non-Hispanic, other race non-Hispanic, and multiple races. In the 2022 survey, there are six race/ethnicity categories: Hispanic, white non-Hispanic, black non-Hispanic, Asian non-Hispanic, American Indian non-Hispanic, and Pacific Islander non-Hispanic/multiple races.

Income inequality is measured using the Theil index (Theil, 1967). The Theil index has also been applied in health services research to quantify inequalities in healthcare resources across geographic regions (Dong et al., 2021; Hou and Wang, 2024; Yin et al., 2025). The Theil index is additively decomposable, allowing overall inequality to be expressed as the sum of within-group and between-group components. As a member of the generalized entropy (GE) class of inequality measures, the Theil index corresponds to GE(1). The Theil index is given by the following equation:

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[2] U.S. Department of Labor, Women's Bureau. *Most Common Occupations of Women in the Labor Force.* https://www.dol.gov/agencies/wb/data/occupations/most-common-occupations-women-labor-force

[3] Analysis is based on 49 state-level units defined by the NSSRN. To preserve respondent anonymity, the NSSRN aggregates specific jurisdictions into combined units: Delaware is combined with the District of Columbia, and Montana is combined with Wyoming. The remaining 47 units represent individual U.S. states.

$$T = \sum_{i=1}^{N} s_i \ln(N s_i)$$

Where:

$s_i = \frac{y_i}{Y}$ *is the income share of individual i*

y_i *is the income of individual i*

$Y = \sum_{i=1}^{N} y_i$ *is total income*

N = Number of individuals

The Theil index has intuitive benchmark properties. It equals zero under perfect equality and reaches its maximum value of ln(*N*) when a single individual earns all income. Individuals with income above the mean contribute positively to the value of the index, while individuals with income below the mean contribute negatively (offsetting positive contributions). Individuals earning exactly the mean do not affect the index. Despite negative individual terms, the Theil index is always nonnegative in aggregate.

A key advantage of the Theil index is that it is additively decomposable across mutually exclusive and exhaustive groups g = 1, 2,…G (e.g., sex, race/ethnicity, education), allowing total earnings inequality to be separated into within-group and between-group components. In other words, it is possible to quantify how much earnings inequality arises from differences in mean earnings between groups (between-group inequality) versus earnings dispersion within groups (within-group inequality). The Theil index decomposition is given by:

$$T = T_{Between} + T_{Within} = \sum_{g=1}^{G} s_g ln\left(\frac{s_g}{N_g/N}\right) + \sum_{g=1}^{G} s_g T_g$$

Where:

$s_g = \frac{Y_g}{Y}$ *is group g's share of total income*

Y_g *is total income of group g*

Y is total income of the full sample

N is the total number of individuals

N_g is the number of individuals in group g

T_g *is the Theil index of individuals within group g*

The first term captures between-group inequality, arising from differences in mean income across groups, while the second term captures within-group inequality, defined as the income-share-weighted average of inequality within groups. As emphasized by Conceiçao and Ferreira (2000), the intuition behind the Theil index is that it measures discrepancies between the distribution of income and the distribution of population across groups. The between-group component compares each group's share of total income (s_g) with its population share (N_g/N). When a group's income share equals its population share, its contribution to between-group inequality is zero; if this holds for all groups, between-group inequality is zero. More generally, between-group inequality increases as groups' income shares diverge from their population shares, which occurs when mean earnings differ substantially across groups.

Although the Theil index is attractive because of its additive decomposability, it is one member of the generalized entropy family of inequality measures. Different measures place different weights on different parts of the earnings distribution. To examine whether the results depend on the choice of inequality measure, I repeat the analysis using GE(0) and GE(2) in Section 5. As with any group-based decomposition, the estimated between-group component depends on the choice of grouping variables. In this paper, the decomposition categories (sex, race/ethnicity, education, employment setting, and geography) were selected because the nursing earnings literature has examined how earnings vary across these demographic and labor market characteristics.

The Theil index was calculated in Stata using the user-written command *ineqdeco*. All estimates apply the person-level survey weights provided by the NSSRN to produce nationally representative results. Sampling uncertainty is quantified using the replicate weights provided by the NSSRN. The 2018 NSSRN uses 100 jackknife replicate weights, while the 2022 NSSRN uses 80 Successive Differences Replication (SDR) weights. These replicate weights are used to compute standard errors for the Theil index and its decomposition components.

4. Results

Table I reports Theil T (GE(1)) measures of annual earnings inequality among registered nurses using the 2022 NSSRN (Panel A) and the 2018 NSSRN (Panel B). In the 2022 NSSRN, the Theil index for annual earnings equals 0.128 (SE = 0.010; 95% CI: [0.108, 0.148]). The corresponding estimate for 2018 is 0.120 (SE = 0.002; 95% CI: [0.115, 0.124]). Thus, earnings inequality among nurses appears somewhat higher in 2022 than in 2018, although the overall structure of inequality across decompositions is qualitatively similar.

Table I. Decomposition of RN Earnings Inequality

Panel A. 2022 NSSRN

Grouping	Theil T	SE(T)	Between GE1	SE(Between)	Between Share (%)	SE(Between Share)
Sex	0.127945	0.010363	0.002646	0.002326	2.07	1.80
Race/Ethnicity	0.127945	0.010363	0.001709	0.001489	1.34	1.15
Race/Ethnicity × Sex	0.127945	0.010363	0.004415	0.002667	3.45	2.06
Education	0.127966	0.010376	0.010159	0.003317	7.94	2.63
Employment Setting	0.127945	0.010363	0.001727	0.001347	1.35	1.03
State	0.127945	0.010363	0.010307	0.004410	8.06	3.41

Panel B. 2018 NSSRN

Grouping	Theil T	SE(T)	Between GE1	SE(Between)	Between Share (%)	SE(Between Share)
Sex	0.119845	0.002374	0.001976	0.000344	1.65	0.28
Race/Ethnicity	0.119845	0.002374	0.002129	0.000367	1.78	0.32
Race/Ethnicity × Sex	0.119845	0.002374	0.004094	0.000470	3.42	0.40
Education	0.119766	0.002378	0.010145	0.000805	8.47	0.65
Employment Setting	0.119845	0.002374	0.000751	0.000215	0.63	0.18
State	0.119845	0.002374	0.011653	0.000919	9.72	0.74

Notes: The table reports Theil T (GE(1)) decompositions using NSSRN data. Standard errors are replicate-weight SEs computed using 80 SDR replicate weights in 2022 and 100 jackknife replicate weights in 2018. Between share is expressed as a percentage of total inequality, and SE(Between share) is in percentage points. Sample sizes differ slightly by grouping due to missing values in the decomposition variables. In the 2018 NSSRN, the education decomposition excludes 23 observations with missing education data (N = 43,741 vs. 43,764), so the total Theil index in that row is calculated on a slightly smaller sample. Likewise, in the 2022 NSSRN, the education decomposition excludes 26 observations with missing education data (N = 40,966 vs. 40,992)

Decomposing inequality by sex indicates that differences in mean earnings between male and female nurses account for only a small fraction of total inequality. In 2022, the between-sex component equals 0.00265, corresponding to a between-sex share of 2.07% of total inequality (SE = 1.80 percentage points; 95% CI: [−1.46%, 5.60%]). This estimate is imprecise and not statistically significant from zero. In 2018, the between-sex share is 1.65% (SE = 0.28 pp; 95% CI: [1.10%, 2.20%]). The estimates are substantially more precise in 2018.[4] These results indicate that nearly all earnings inequality in nursing reflects dispersion within sexes rather than differences in average earnings across sexes. In 2022, the population-weighted mean annual earnings for male and female nurses were $104,283 and $84,772, respectively.

Table I also reports the decomposition of earnings inequality across race/ethnicity categories. The between-race component explains only a small fraction of total inequality. In 2022, the between-race share equals 1.34% of total inequality (SE = 1.15 pp; 95% CI: [-0.91%, 3.59%]). Results for 2018 are similar in magnitude, with the between-race share equal to 1.78% (SE = 0.32 pp; 95% CI: [1.15%, 2.41%]). The estimates are more precisely estimated in 2018. Although racial/ethnic earnings gaps may exist at the level of mean earnings, they account for only a limited share of overall earnings inequality among nurses.

[4] Standard errors are generally larger in the 2022 NSSRN than in 2018 which may reflect differences in variance estimation. The 2022 NSSRN uses the Successive Differences Replication (SDR) method with 80 replicate weights, whereas the 2018 NSSRN used a jackknife method with 100 replicate weights. These differences affect the precision of the variance estimates but do not affect the point estimates.

The intersectional decomposition by race/ethnicity and sex yields a larger between-group component than either decomposition alone. In the 2022 NSSRN, this decomposition partitions the sample into 12 race–sex groups (six race/ethnicity categories by two sexes), and the between-group share rises to 3.45% of total inequality (SE = 2.06 pp; 95% CI: [-0.59%, 7.49%]). A similar pattern emerges in the 2018 NSSRN (between share = 3.42%, SE = 0.40 pp; 95% CI: [2.64%, 4.20%]), which is precisely estimated. By decomposing earnings jointly by race/ethnicity and sex, I account for the possibility that demographic characteristics interact rather than operate independently. Recent labor economics research defines intersectional discrimination as arising when the combined earnings penalty associated with race and sex exceeds the sum of the separate penalties (McLaughlin and Neumark, 2025). Although the race/ethnicity-by-sex decomposition yields a larger between-group component than considering race or sex separately, between-group differences still account for only a small share of total earnings inequality, reinforcing the central finding that most RN earnings inequality occurs within demographic groups.

Table I further reports inequality decompositions by educational attainment, measured using the nurse's highest nursing degree. Education accounts for one of the largest between-group shares, yielding a between-education share of 7.94% in 2022 (SE = 2.63 pp; 95% CI: [2.79%, 13.10%]). In 2018, the between-education share is 8.47% (SE = 0.65 pp; 95% CI: [7.20%, 9.74%]). Both estimates are statistically significant from zero. Thus, differences in mean earnings by education contribute more to overall inequality than do sex, race/ethnicity, or race/ethnicity-by-sex groupings. Nevertheless, even education explains less than one-tenth of total inequality, implying that substantial earnings dispersion persists among nurses with the same educational credentials.

Table I also reports the decomposition by employment setting, distinguishing hospital-based employment from non-hospital settings. In 2022, the between-setting component accounts for 1.35% of total inequality (SE = 1.03 pp; 95% CI: [-0.67%, 3.37%]). In 2018, the corresponding between-setting share is smaller, at 0.63% (SE = 0.18 pp; 95% CI: [0.28%, 0.98%]). In sum, employment setting contributes negligibly to overall earnings inequality among nurses.

Finally, geography—measured by state of employment—accounts for an economically meaningful share of earnings inequality. In the 2022 NSSRN, the between-state share equals 8.06% of total inequality (SE = 3.41 pp; 95% CI: [1.38%, 14.74%]), while the 2018 estimate is 9.72% (SE = 0.74 pp; 95% CI: [8.27%, 11.17%]). Both estimates are statistically distinguishable from zero. In both years, the magnitude of the between-state component is comparable to that of the education decomposition, although the majority of inequality remains within states. These geographic differences likely reflect variation in local cost of living, state-level labor market conditions, and institutional factors, such as unionization and regulatory environments. This suggests substantial earnings dispersion among nurses across state lines; for example, population-weighted mean annual earnings ranged from a high of $119,835 in California to a low of $69,460 in Iowa.

Overall, across all decompositions, within-group inequality accounts for over 90% of total inequality—and, with the exception of geography, typically exceeds 96%. These results indicate that between-group differences explain only a limited portion of earnings dispersion among registered nurses. The findings are consistent with Galor and Wainstock (2025), who examine

inequality across the broader workforce and find that only about 4% of total income inequality is attributable to differences between groups.

5. Robustness to Alternative Measures of Earnings Inequality

I examine the sensitivity of the main results using two alternative GE inequality measures, GE(0) and GE(2). Whereas the Theil index, GE(1), applies proportional weights across the earnings distribution, GE(0) places relatively greater weight on the lower end of the distribution, while GE(2) places relatively greater weight on the upper end. Table II reports the between-group shares of earnings inequality using the GE(0) and GE(2) measures for 2018 and 2022. The qualitative conclusions remain unchanged. The shares of inequality attributable to differences in sex, race/ethnicity, race/ethnicity-by-sex interactions, and employment setting remain small in both years. As with the Theil index, education and geography account for the largest between-group components of earnings inequality, although even under GE(2), the between-group share for education reaches only about 10% in 2018. The main finding that most earnings inequality occurs within rather than between observable groups is robust to different generalized entropy measures.

Table II. Between-Group Shares of Earnings Inequality (%): GE(0) and GE(2)

Grouping	2018 GE(0)	2018 GE(2)	2022 GE(0)	2022 GE(2)
Sex	1.06	1.73	1.27	2.16
Race/Ethnicity	1.15	1.85	0.85	1.35
Race/Ethnicity × Sex	2.22	3.55	2.16	3.54
Education	5.39	9.02	4.84	8.42
Employment Setting	0.43	0.62	0.88	1.33
State	6.26	10.26	4.97	8.46

Notes: Entries report the percentage of total earnings inequality attributable to between-group differences.

6. Supplemental Results: Hourly Wage Inequality

To evaluate whether annual earnings inequality reflects variation in work hours rather than compensation rates, supplemental analyses examine hourly wage inequality, defined as annual salary divided by total annual hours worked. To reduce measurement noise and ensure that hourly wages reflect meaningful labor supply, the hourly wage analysis restricts the sample to nurses working at least 1,000 hours during the year.[5]

[5] Results are qualitatively similar when using a 500-hour threshold.

Table III reports Theil T (GE(1)) measures of hourly wage inequality using the 2022 NSSRN (Panel A) and the 2018 NSSRN (Panel B). Overall, hourly wage inequality is lower than annual earnings inequality; for example, in the 2022 NSSRN, the Theil index for annual earnings is 0.128 (SE = 0.009), compared to 0.092 (SE = 0.001) for hourly wages. This disparity is expected, as annual earnings inequality captures the joint variation of both wage rates and labor supply (hours worked), whereas the hourly wage measure normalizes for the latter.

Table III. Decomposition of RN Hourly Wage Inequality

Panel A. 2022 NSSRN

Grouping	Theil T	SE(T)	Between GE1	SE(Between)	Between Share (%)	SE(Between Share)
Sex	0.092464	0.009286	0.000977	0.001379	1.06	1.487
Race/Ethnicity	0.092464	0.009286	0.001034	0.001158	1.118	1.233
Race/Ethnicity × Sex	0.092464	0.009286	0.002045	0.001726	2.212	1.839
Education	0.092476	0.009290	0.004866	0.002042	5.262	2.293
Employment Setting	0.092464	0.009286	0.002927	0.001734	3.165	1.844
State	0.092464	0.009286	0.011523	0.004881	12.462	4.937

Panel B. 2018 NSSRN

Grouping	Theil T	SE(T)	Between GE1	SE(Between)	Between Share (%)	SE(Between Share)
Sex	0.080039	0.001777	0.000421	0.000119	0.526	0.147
Race/Ethnicity	0.080039	0.001777	0.001437	0.000257	1.796	0.335
Race/Ethnicity × Sex	0.080039	0.001777	0.001895	0.000281	2.368	0.367
Education	0.080095	0.001774	0.006467	0.000435	8.074	0.533
Employment Setting	0.080039	0.001777	0.000646	0.000145	0.808	0.182
State	0.080039	0.001777	0.012412	0.000686	15.508	0.784

Notes: The table reports Theil T (GE(1)) decompositions using NSSRN data. Standard errors are replicate-weight SEs computed using 80 SDR replicate weights in 2022 and 100 jackknife replicate weights in 2018. Between share is expressed as a percentage of total inequality, and SE(Between share) is in percentage points. Sample sizes differ slightly by grouping due to missing values in the decomposition variables. In the 2018 NSSRN, the education decomposition excludes 17 observations with missing education data (N = 40,595 vs. 40,612), so the total Theil index in that row is calculated on a slightly smaller sample. Likewise, in the 2022 NSSRN, the education decomposition excludes 24 observations with missing education data (N= 36,976 vs. 37,000).

In both 2018 and 2022, the between-group share is small for sex, race/ethnicity, their interaction, and employment setting (hospital vs. non-hospital); these results are qualitatively similar to the decompositions based on annual earnings. None of these dimensions explains more than 3.2% of total hourly wage inequality, indicating that the vast majority of dispersion occurs within groups. While the 2022 between-group shares are generally imprecisely estimated, the 2018 estimates exhibit significantly greater precision.

For education, within-group inequality accounts for approximately 92% to 95% of total hourly wage inequality, with only 5% to 8% attributable to differences in mean wages across education groups. In both years, these between-education shares are statistically significant at conventional levels.

Finally, Table III indicates that the largest between-group component arises from geographic location. Between-state differences account for 12.5% of hourly wage inequality in 2022 and 15.5% in 2018. These shares are larger than the corresponding between-state shares for annual earnings (approximately 8% to 10%), so geographic location accounts for a larger share of inequality for hourly wages than for annual earnings.[6] This occurs because annual earnings incorporate substantial within-state variation in hours worked. When inequality is measured using hourly wages, the hours-worked component is removed, reducing within-state dispersion and lowering the overall inequality index. Because cross-state differences in pay rates remain, the between-state component represents a larger fraction of the smaller total inequality. Overall, the hourly wage decompositions suggest that geographic pay differences contribute more strongly to wage inequality than demographic group differences, pointing toward the importance of regional labor market institutions and wage-setting environments.

7. Conclusion

The Theil decompositions indicate that most RN earnings inequality reflects dispersion within demographic groups rather than differences in mean earnings across groups. Sex and race/ethnicity explain only a small share of total inequality, while education and geography account for comparatively larger between-group components.

Across all decompositions, within-group inequality accounts for the overwhelming majority of total inequality and typically exceeds 96%. These findings are consistent with broader evidence showing that most overall income inequality reflects within-group rather than between-group dispersion (Galor and Wainstock, 2025).

Overall, the results suggest substantial earnings heterogeneity among nurses within narrowly defined demographic and labor market groups.

[6] Across 49 states, the mean within-state Theil index is 0.090 for annual earnings versus 0.080 for hourly wages. Within-state inequality is lower for hourly wages in 43 of 49 states (88%), a pattern consistent with the hypothesis that variation in hours worked is an important factor of the higher dispersion observed in annual earnings.

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