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RESEARCH

# Multimorbidity patterns by payer status: More challenges, more opportunities

Byron S Kennedy, Robert P Richeson, Amy J Houde

Health Services Unit, Connecticut Department of Correction, Wethersfield, CT, USA

**SUMMARY**

We examined how health payer status influences patterns of coexisting chronic diseases in US adults. Participants in safety-net programs showed higher multimorbidity rates, while the uninsured exhibited the strongest disease clustering. This clustering intensified with more coexisting conditions, suggesting shared underlying pathways. Clinicians may improve outcomes by targeting these shared mechanisms—particularly metabolic dysfunction—through integrated preventive care.

**Key Words:** Multimorbidity; health services accessibility; Veteran's health; indigenous health; prison health

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**Corresponding Author:** Byron S Kennedy (byron.kennedy@ct.gov): Health Services Unit, Connecticut Department of Correction, Wethersfield, CT, USA

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## ABSTRACT

### Background

Managing multiple noncommunicable diseases (NCDs) is a major challenge for clinicians and health systems. Understanding how multimorbidity patterns vary by payer status may inform better care for safety-net populations.

### Aims

To assess multimorbidity patterns among nonelderly US adults by health payer status.

### Method

Using pooled data from the National Health Interview Survey (2016–2018) and the Survey of Prison Inmates (2016), we examined NCD clustering across payer groups: private, uninsured, Medicaid, Indian Health Service (IHS), Veterans Health Administration (VHA), and prison coverage. We estimated adjusted multimorbidity rates via negative binomial regression and assessed clustering strength using observed-to-expected prevalence ratios.

### Conclusion

Among 75,551 participants representing 177 million adults, multimorbidity rates were highest for the Medicaid and VHA groups. Disease clustering was strongest among uninsured adults and weakest among VHA participants. Triads (three coexisting NCDs) showed stronger clustering than dyads (two NCDs). Safety-net enrollees exhibited greater multimorbidity, while uninsured adults showed tighter clustering of NCDs, underscoring gaps in integrated care. Stronger triad clustering suggests shared disease mechanisms—potentially metabolic—highlighting opportunities for targeted lifestyle and preventive interventions.

## BACKGROUND

Multimorbidity—defined as the presence of two or more chronic conditions—has become a global public health issue linked to higher mortality rates and increased costs.[1–7] Although older adults are the most affected, nonelderly adults face increased risk.[8] Socioeconomic disadvantage compounds this burden, with lower-income individuals experiencing higher multimorbidity rates and reduced access to preventive care.[9]

Insurance coverage influences access and health outcomes. A systematic review of 24 studies from five countries found that insured individuals, particularly those with private coverage, generally exhibited healthier lifestyles and lower prevalence of non-communicable diseases (NCD).[10] However, few studies have examined patterns of multimorbidity—specifically, disease clustering—according to payer status. Previous US studies often focused on private coverage (for working-age, employed individuals), Medicare (for the elderly), and Medicaid (for low-income individuals). However, they excluded key safety-net programs such as the Indian Health Service (IHS) for indigenous groups, the Veterans Health Administration (VHA) for former military personnel, and correctional coverage for incarcerated individuals, leaving a significant evidence gap.

Given the variation in eligibility, funding, and services across payer groups, understanding differences in multimorbidity patterns can help promote more integrated and equitable care. We therefore analysed NCD clustering among US adults aged 18–64, stratified by payer status.

## METHOD

### Data Sources

We conducted a population-based cross-sectional analysis using the National Health Interview Survey (NHIS, 2016–2018) and the Survey of Prison Inmates (SPI, 2016).[11,12] Regarding timeliness, prison data are collected less frequently than for the other payers, but the SPI 2016 is the most recent data available from the U.S. Department of Justice. Both are nationally representative, in-person surveys. We combined datasets using super-stratum weighting to align with US population estimates.[13] Adults aged 18–64 were included if they were classified into one of six payer groups: private, uninsured, Medicaid, IHS, VHA, or prison coverage.

### Study Measures

The primary outcome was the number of chronic NCDs per individual. We focused on conditions linked to preventable mortality that were assessed in both surveys (Table 1), such as obesity, diabetes, asthma, heart disease, arthritis, kidney disease, and liver disease. The primary comparison was by payer group. Covariates included age, sex, race/ethnicity (White, Black, Hispanic, Asian, American Indian/Alaska Native), nativity, education (≤12 vs. ≥13 years), and income-to-poverty ratio (<1.0, 1.0–2.99, ≥3.0). For incarcerated participants, poverty status was estimated based on maximum compensation during incarceration.[14]

### Study Analysis

Group comparisons used chi-square and t-tests; significance was set at $p<0.05$. To model multimorbidity, we applied negative binomial regression, given preliminary evidence of overdispersion, estimating rate ratios (RRs) and 95% confidence intervals (CIs).[15,16] Disease clustering was assessed using observed-to-expected ratios (OERs) (also called "lift").[17] We calculated OERs for the most common dyads (two coexisting NCDs) and triads (three NCDs) across payer groups. The expected prevalence assumed that chronic conditions occurred independently of each other. For example, the OER for the obesity-hypertension dyad:

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OER = Probability (obesity and hypertension) / [Probability (obesity) x Probability (hypertension)].

Values >1 indicate stronger-than-expected clustering. Analyses accounted for complex survey design using Stata 18's *svy* module (College Station, TX).

## RESULTS

### Study Population

The pooled dataset included 75,551 participants representing 177 million adults (mean age 40.5 years; 49.8 per cent female; 38.5 per cent non-White; 13 per cent below the poverty line) (Table 2). The distribution by payer was as follows: private (71.6 per cent), uninsured (12.6 per cent), Medicaid (13.6 per cent), IHS (0.4 per cent), VHA (1.1 per cent), and prison (0.7 per cent). Obesity was the most common condition (range 28.6 per cent–51.0 per cent), while liver and kidney disease were the least prevalent (<1 per cent). The mean number of NCDs ranged from 0.9 (uninsured) to 1.8 (VHA).

### Regression Model

The adjusted regression model (Table 3, Figure 1) showed the highest multimorbidity rates among Medicaid (RR 1.4, 95% CI 1.4–1.5) and VHA (RR 1.4, 95% CI 1.3–1.5) participants compared with privately insured adults. American Indian/Alaska Native adults had the highest rates by race (RR 1.2), while Asian adults had the lowest (RR 0.7). Higher education, income, foreign birth, and younger age were protective factors ($p<0.001$ for all).

### Disease Clustering

Across all participants, the diabetes–liver disease dyad was the strongest (OER 2.9), while the hypertension–diabetes–heart disease triad was the strongest triad (OER 9.9) (Table 4). By payer, IHS adults had the highest dyad OER (4.7; heart disease–liver disease), and uninsured adults had the highest triad OER (10.3; hypertension–heart disease–arthritis). Triads consistently showed stronger clustering than dyads, with clustering being strongest among the uninsured and weakest among VHA participants (Figure 2).

## DISCUSSION

This national analysis reveals clear differences in multimorbidity and NCD clustering by payer status among nonelderly adults. Safety-net participants (Medicaid, IHS, and VHA) experienced higher multimorbidity, while uninsured adults exhibited tighter disease clustering, suggesting less access to coordinated care.

Among safety-net systems, VHA and IHS provide lifetime eligibility and dedicated clinical networks. However, federal per-capita funding differs substantially—about $13,400 for VHA versus $3,500 for IHS—potentially explaining the weaker clustering among VHA members.[18,19] VHA's integrated model may support continuity and chronic disease coordination, which is reflected in better patient outcomes and satisfaction.[20,21]

Uninsured adults showed both lower multimorbidity rates and stronger clustering, likely due to undiagnosed conditions and limited access to preventive care.[22] Financial barriers, employment-related coverage gaps, and immigration restrictions may worsen these risks. This study found that poverty and foreign-born status are common among uninsured adults.

Prison populations showed lower multimorbidity rates but similar clustering to privately insured adults. Incarcerated individuals are restricted from participating in federal safety-net programmes while they are in correctional facilities.[23] However, prisons likely have access to primary care and preventive services, but coordination of NCD care with specialty services may be limited due to transfers, re-entry, and specialty availability.

Managing multimorbidity is challenging, and worsening trends in metabolic syndrome suggest these challenges will persist.[24–26] The strong clustering of NCDs—especially triads—may indicate shared pathophysiological pathways rather than independent conditions. Metabolic dysfunction likely underlies much of this overlap.[27] Prior metabolomics studies identified hundreds of shared metabolites across cardiometabolic, renal, and respiratory diseases, suggesting that integrated metabolic management may improve multiple conditions simultaneously.[28–30]

Our findings underscore the need for integrated, prevention-oriented care across payer systems. Programs emphasising metabolic health, nutrition, physical activity, and smoking cessation could mitigate NCD clustering. VHA's structured wellness services (eg, health coaching, dietitian access) may serve as a model.[20] Expanding similar programmes within Medicaid and IHS could enhance long-term outcomes, while addressing insurance gaps remains essential for reducing clustering among the uninsured.

## LIMITATIONS

This study has notable strengths. First, to our knowledge, this is the first population-based analysis comparing multimorbidity and NCD clustering across six major payer groups, including safety-net and correctional programs; therefore, we address an important gap in the literature. Second, examining dyad versus triad patterns offers novel insights into shared disease mechanisms. Third, modelling multimorbidity as a full count distribution provides more granularity than dichotomous definitions and adjustment for key covariates support the robustness of our findings. Finally, the inclusion of both NHIS and SPI enhances representativeness.

Several limitations should be considered. First, self-report bias: conditions were self-reported, possibly underestimating true prevalence. Second, lack of clinical detail: prevalence does not account for disease onset, duration, severity, or survival, although multimorbidity is linked with a higher mortality risk. Third, cross-sectional design: data reflect one time point; causal inference is not possible (e.g., possible reverse causation, residual confounding). Fourth, restricted condition list: only NCDs assessed in both surveys were analysed, limiting comprehensiveness and generalisability, but ensuring comparability. Fifth, temporal limitations: the latest SPI data (2016) may not capture recent trends (eg, federal policy changes that may increase resources for VHA and IHS but limit safety-net access for foreign-born, work-eligible men). Sixth, potential misclassification: estimating poverty among incarcerated participants may underestimate socioeconomic hardship.

## CONCLUSION

Multimorbidity patterns among nonelderly US adults differ markedly by payer status. Safety-net participants face higher multimorbidity burdens, while uninsured adults experience tighter disease clustering—indicating unmet needs for coordinated care. The strong clustering of triads points to shared metabolic pathways underlying multiple NCDs. Investments in integrated, prevention-based strategies—especially within Medicaid, IHS, and among uninsured populations—may improve outcomes and reduce disparities. Future research should explore metabolic and social determinants of clustering to inform holistic, cost-effective care models.

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## PEER REVIEW

Not commissioned. Externally peer reviewed.

## CONFLICTS OF INTEREST

The authors declare that they have no competing interests.

## FUNDING

None

## ETHICS COMMITTEE APPROVAL

For the analysis, we used only deidentified, publicly available data; therefore, IRB approval was not required.  We present only aggregate results; therefore, informed consent was not required.

## DATA AVAILABILITY

For the analysis, we used only deidentified, publicly available data, which researchers may obtain from the US Centers for Disease Control and Prevention and the US Bureau of Justice Statistics.

**Table 1: Chronic condition specification in study surveys**

| Variable | NHIS 2016–2018 | SPI 2016 |
| --- | --- | --- |
| Obesity | Body mass index (BMI) ≥ 30 kg/m$^2$ | Body mass index (BMI) ≥ 30 kg/m$^2$ |
| Hypertension | “High blood pressure” or “Hypertension” | “High blood pressure” or “Hypertension” |
| Diabetes | “Diabetes” | “Diabetes, high blood sugar, or sugar diabetes” |
| Heart disease | “Heart condition/disease (including heart failure),” or “heart attack,” or “coronary heart disease,” or “angina pectoris” | “Heart disease, including heart attack, coronary heart disease, angina, congestive heart failure or other heart problems” |
| Stroke | “Stroke” | “Stroke” |
| Kidney disease | “Weak/failing kidneys past 12 months” | “Current kidney problems” |
| Cancer | “Cancer” | “Cancer” |
| Asthma | “Asthma/breathing problems” | “Asthma” |
| Arthritis | “Arthritis, rheumatoid arthritis, gout, lupus, fibromyalgia” | “Arthritis, rheumatoid arthritis, gout, lupus, or fibromyalgia” |
| Liver disease | “Chronic/long-term liver condition” | “Cirrhosis of liver” |

NHIS = National Health Interview Survey; SPI = Survey of Prison Inmates
Notes: Question items were selected that had the most similar language for both surveys; for example, the question stem began with “Ever told/had” for all non-obesity conditions except for kidney disease, which used “past 12 months” and “current” for the NHIS and SPI, respectively.

**Table 2: Study population summary characteristics, United States, 2016–2018**

| | | Payer Group | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Overall** | **Private** | **Uninsured** | **Medicaid** | **IHS** | **VHA** | **Prison** | ***P*-value** |
| N, weighted | 177,482,234 (100.0%) | 127,133,103 (71.6%) | 22,404,814 (12.6%) | 24,116,019 (13.6%) | 710,456 (0.4%) | 1,919,436 (1.1%) | 1,198,406 (0.7%) | |
| Age, mean (SD) | 40.5 (9.5) | 41.4 (8.1) | 38.2 (7.5) | 38.1 (8.4) | 40.7 (9.5) | 46.9 (8.3) | 38.2 (49.9) | <0.001 |
| *Sex* | | | | | | | | |
| Men | 89,174,882 (50.2%) | 64,305,221 (50.6%) | 12,578,045 (56.1%) | 9,188,364 (38.1%) | 356,797 (50.2%) | 1,630,534 (84.9%) | 1,115,921 (93.1%) | <0.001 |
| Women | 88,307,352 (49.8%) | 62,827,882 (49.4%) | 9,826,769 (43.9%) | 14,927,655 (61.9%) | 353,659 (49.8%) | 288,902 (15.1%) | 82,486 (6.9%) | |
| *Race/Ethnicity* | | | | | | | | |
| White | 109,209,694 (61.5%) | 86,815,752 (68.3%) | 9,651,577 (43.1%) | 11,014,901 (45.7%) | 32,027 (4.5%) | 1,291,408 (67.3%) | 404,029 (33.7%) | NA |
| Black | 22,315,420 (12.6%) | 13,258,845 (10.4%) | 3,162,304 (14.1%) | 5,043,175 (20.9%) | 5,889 (0.8%) | 389,827 (20.3%) | 455,379 (38.0%) | |
| Hispanic | 32,919,670 (18.5%) | 17,405,492 (13.7%) | 8,563,502 (38.2%) | 6,404,277 (26.6%) | 52,220 (7.4%) | 188,662 (9.8%) | 305,518 (25.5%) | |
| Asian | 11,553,134 (6.5%) | 9,206,751 (7.2%) | 878,231 (3.9%) | 1,419,315 (5.9%) | 0 (0.0%) | 34,861 (1.8%) | 13,976 (1.2%) | |
| AIAN[c] | 1,484,316 (0.8%) | 446,263 (0.4%) | 149,200 (0.7%) | 234,351 (1.0%) | 620,320 (87.3%) | 14,678 (0.8%) | 19,505 (1.6%) | |
| *US Born* | | | | | | | | |
| Yes | 141,349,837 (79.6%) | 104,984,546 (82.6%) | 14,169,091 (63.2%) | 18,618,460 (77.2%) | 703,786 (99.1%) | 1,804,647 (94.0%) | 1,069,307 (89.2%) | <0.001 |
| No | 36,132,397 (20.4%) | 22,148,557 (17.4%) | 8,235,723 (36.8%) | 5,497,559 (22.8%) | 6,670 (0.9%) | 114,789 (6.0%) | 129,099 (10.8%) | |
| *Education* | | | | | | | | |
| 0–12 years | 60,835,442 (34.3%) | 31,077,286 (24.4%) | 13,204,771 (58.9%) | 14,577,098 (60.4%) | 371,410 (52.3%) | 561,069 (29.2%) | 1,043,809 (87.1%) | <0.001 |
| 13+ years | 116,646,792 (65.7%) | 96,055,817 (75.6%) | 9,200,043 (41.1%) | 9,538,921 (39.6%) | 339,046 (47.7%) | 1,358,366 (70.8%) | 154,598 (12.9%) | |
| *Poverty Ratio* | | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| < 1.00 | 23,124,878 (13.0%) | 6,029,284 (4.7%) | 5,419,210 (24.2%) | 9,995,707 (41.4%) | 208,754 (29.4%) | 273,517 (14.2%) | 1,198,406 (100.0%) | NA |
| 1.00 – 2.99 | 54,157,348 (30.5%) | 30,056,136 (23.6%) | 11,501,765 (51.3%) | 11,520,777 (47.8%) | 331,469 (46.7%) | 747,200 (38.9%) | 0 (0.0%) | |
| ≥ 3.00 | 100,200,008 (56.5%) | 91,047,683 (71.6%) | 5,483,838 (24.5%) | 2,599,535 (10.8%) | 170,233 (24.0%) | 898,718 (46.8%) | 0 (0.0%) | |
| *Obesity* | | | | | | | | |
| 0 | 122,881,891 (69.2%) | 90,231,848 (71.0%) | 15,274,459 (68.2%) | 15,042,971 (62.4%) | 348,410 (49.0%) | 1,128,679 (58.8%) | 855,524 (71.4%) | <0.001 |
| 1 | 54,600,343 (30.8%) | 36,901,255 (29.0%) | 7,130,354 (31.8%) | 9,073,049 (37.6%) | 362,046 (51.0%) | 790,757 (41.2%) | 342,882 (28.6%) | |
| *Hypertension* | | | | | | | | |
| 0 | 137,944,718 (77.7%) | 99,831,622 (78.5%) | 18,509,810 (82.6%) | 17,157,192 (71.1%) | 472,248 (66.5%) | 1,100,938 (57.4%) | 872,908 (72.8%) | <0.001 |
| 1 | 39,537,516 (22.3%) | 27,301,481 (21.5%) | 3,895,004 (17.4%) | 6,958,828 (28.9%) | 238,208 (33.5%) | 818,498 (42.6%) | 325,498 (27.2%) | |
| *Diabetes* | | | | | | | | |
| 0 | 166,190,338 (93.6%) | 120,197,819 (94.5%) | 21,168,956 (94.5%) | 21,458,647 (89.0%) | 565,289 (79.6%) | 1,686,370 (87.9%) | 1,113,257 (92.9%) | <0.001 |
| 1 | 11,291,896 (6.4%) | 6,935,284 (5.5%) | 1,235,858 (5.5%) | 2,657,373 (11.0%) | 145,167 (20.4%) | 233,066 (12.1%) | 85,149 (7.1%) | |
| *Heart* | | | | | | | | |
| 0 | 165,140,083 (93.0%) | 119,090,552 (93.7%) | 21,172,755 (94.5%) | 21,513,690 (89.2%) | 641,608 (90.3%) | 1,594,959 (83.1%) | 1,126,519 (94.0%) | <0.001 |
| 1 | 12,342,151 (7.0%) | 8,042,551 (6.3%) | 1,232,059 (5.5%) | 2,602,330 (10.8%) | 68,848 (9.7%) | 324,477 (16.9%) | 71,887 (6.0%) | |
| *Stroke* | | | | | | | | |
| 0 | 174,851,094 (98.5%) | 125,942,226 (99.1%) | 22,111,354 (98.7%) | 23,095,491 (95.8%) | 695,790 (97.9%) | 1,835,327 (95.6%) | 1,170,907 (97.7%) | <0.001 |
| 1 | 2,631,140 (1.5%) | 1,190,877 (0.9%) | 293,460 (1.3%) | 1,020,529 (4.2%) | 14,666 (2.1%) | 84,109 (4.4%) | 27,500 (2.3%) | |
| *Kidney* | | | | | | | | |
| 0 | 175,506,369 (98.9%) | 126,208,701 (99.3%) | 22,204,050 (99.1%) | 23,370,965 (96.9%) | 690,268 (97.2%) | 1,862,194 (97.0%) | 1,170,190 (97.6%) | <0.001 |
| 1 | 1,975,865 (1.1%) | 924,402 (0.7%) | 200,763 (0.9%) | 745,054 (3.1%) | 20,188 (2.8%) | 57,241 (3.0%) | 28,216 (2.4%) | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Cancer* | | | | | | | | |
| 0 | 168,496,186 (94.9%) | 120,291,518 (94.6%) | 21,834,923 (97.5%) | 22,761,497 (94.4%) | 679,943 (95.7%) | 1,764,308 (91.9%) | 1,163,996 (97.1%) | <0.001 |
| 1 | 8,986,048 (5.1%) | 6,841,585 (5.4%) | 569,890 (2.5%) | 1,354,523 (5.6%) | 30,513 (4.3%) | 155,127 (8.1%) | 34,410 (2.9%) | |
| *Asthma* | | | | | | | | |
| 0 | 152,955,843 (86.2%) | 110,217,023 (86.7%) | 20,049,338 (89.5%) | 19,377,571 (80.4%) | 618,351 (87.0%) | 1,678,355 (87.4%) | 1,015,206 (84.7%) | <0.001 |
| 1 | 24,526,391 (13.8%) | 16,916,080 (13.3%) | 2,355,476 (10.5%) | 4,738,449 (19.6%) | 92,105 (13.0%) | 241,081 (12.6%) | 183,200 (15.3%) | |
| *Arthritis* | | | | | | | | |
| 0 | 149,196,009 (84.1%) | 107,776,150 (84.8%) | 19,999,077 (89.3%) | 18,670,291 (77.4%) | 582,884 (82.0%) | 1,150,893 (60.0%) | 1,016,715 (84.8%) | <0.001 |
| 1 | 28,286,225 (15.9%) | 19,356,953 (15.2%) | 2,405,737 (10.7%) | 5,445,728 (22.6%) | 127,572 (18.0%) | 768,543 (40.0%) | 181,691 (15.2%) | |
| *Liver* | | | | | | | | |
| 0 | 175,443,667 (98.9%) | 126,029,076 (99.1%) | 22,203,641 (99.1%) | 23,498,978 (97.4%) | 689,114 (97.0%) | 1,843,575 (96.0%) | 1,179,283 (98.4%) | <0.001 |
| 1 | 2,038,566 (1.1%) | 1,104,027 (0.9%) | 201,173 (0.9%) | 617,041 (2.6%) | 21,342 (3.0%) | 75,861 (4.0%) | 19,123 (1.6%) | |
| *Conditions,* mean (SD) | 1.0 (0.9) | 1.0 (0.7) | 0.9 (0.6) | 1.5 (0.9) | 1.6 (1.1) | 1.8 (1.1) | 1.1 (5.7) | <0.001 |

IHS = Indian Health Service; VHA = Veterans Health Administration; AIAN = American Indian/Alaska Native; N/A = not applicable; 0 = No; 1 = Yes

Notes: Continuous variables are reported as the weighted mean (SD) and comparisons are made using the t-test; categorical variables are reported as the weighted frequency (%) and comparisons are made using the Chi square test; percentages may not sum to 100% due to rounding; differences were considered statistically significant for a two-sided *p*-value < 0.05; Chi square test was not applicable for cells with sampling zeros (IHS vs Asian, prison vs poverty ratio 1.00 – 2.99, ≥ 3.00); the analysis was performed using Stata 18 (College Station, TX).

**Table 3: Negative binomial regression model of the number of chronic conditions, United States, 2016–2018**

| | RR | [95% CI] | | *P*-value |
|---|---|---|---|---|
| *Payer* | | | | |
| Private | Reference | | | |
| Uninsured | 0.94 | 0.91 | 0.98 | 0.007 |
| Medicaid | 1.42 | 1.37 | 1.47 | < 0.001 |
| IHS[a] | 1.14 | 0.99 | 1.32 | 0.071 |
| VHA[b] | 1.41 | 1.30 | 1.53 | < 0.001 |
| Prison | 0.95 | 0.91 | 0.99 | 0.025 |
| | | | | |
| *Age, standardised* | 1.54 | 1.52 | 1.56 | < 0.001 |
| | | | | |
| *Sex* | | | | |
| Men | Reference | | | |
| Women | 1.02 | 0.99 | 1.04 | 0.138 |
| | | | | |
| *Race/Ethnicity* | | | | |
| White | Reference | | | |
| Black | 1.10 | 1.07 | 1.14 | < 0.001 |
| Hispanic | 1.06 | 1.02 | 1.11 | 0.006 |
| Asian | 0.74 | 0.68 | 0.80 | < 0.001 |
| AIAN[c] | 1.23 | 1.08 | 1.39 | 0.002 |
| | | | | |
| *US Born* | | | | |
| Yes | Reference | | | |
| No | 0.63 | 0.61 | 0.66 | < 0.001 |
| | | | | |
| *Education* | | | | |

| | | | | |
|---|---|---|---|---|
| 0–12 years | Reference | | | |
| 13+ years | 0.95 | 0.92 | 0.97 | < 0.001 |
| | | | | |
| *Poverty Ratio* | | | | |
| < 1.00 | Reference | | | |
| 1.00– 2.99 | 0.94 | 0.90 | 0.97 | < 0.001 |
| ≥ 3.00 | 0.80 | 0.77 | 0.83 | < 0.001 |

IHS = Indian Health Service; VHA = Veterans Health Administration; AIAN = American Indian/Alaska Native; RR = rate ratio;
CI = confidence interval
Notes: Age was standardized by centring the data to have a mean of zero and standard deviation of one; the analysis was performed using Stata version 18 (College Station, TX).

**Table 4: Multimorbidity Prevalence Patterns with Observed-to-Expected Ratio by Payer Group, United States, 2016–2018**

| | | | | **Observed-to-Expected Ratio (OER)** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Pattern** | **Condition 1** | **Condition 2** | **Condition 3** | **Overall** | **Private** | **Uninsured** | **Medicaid** | **IHS** | **VHA** | **PRISON** |
| DYAD | DIABETES | LIVER | | **2.90** | 2.67 | 3.02 | 1.93 | 1.78 | 1.88 | 2.24 |
| DYAD | HTN | STROKE | | 2.88 | 2.75 | 3.61 | **2.58** | 2.09 | 1.83 | 2.50 |
| DYAD | HEART | LIVER | | 2.83 | 2.44 | 2.15 | 2.22 | **4.71** | **1.95** | 2.46 |
| DYAD | HTN | DIABETES | | 2.80 | **2.83** | 2.97 | 2.43 | 1.85 | 1.78 | 2.60 |
| DYAD | ARTHRITIS | LIVER | | 2.58 | 2.00 | 3.71 | 2.25 | 2.71 | 1.23 | 2.43 |
| DYAD | HEART | ARTHRITIS | | 2.33 | 2.13 | 2.76 | 2.38 | 2.82 | 1.31 | 2.54 |
| DYAD | DIABETES | ARTHRITIS | | 2.29 | 2.18 | 2.58 | 2.09 | 1.44 | 1.76 | 2.27 |
| DYAD | HTN | LIVER | | 2.22 | 1.98 | 1.89 | 1.90 | 0.50 | 1.73 | 1.81 |
| DYAD | HEART | CANCER | | 2.21 | 2.08 | **4.02** | 2.22 | 4.47 | 1.23 | **3.30** |
| DYAD | HTN | HEART | | 2.20 | 2.10 | 2.52 | 2.17 | 1.49 | 1.58 | 2.35 |
| DYAD | CANCER | ARTHRITIS | | 2.17 | 2.12 | 2.66 | 2.13 | 3.23 | 1.17 | 2.40 |
| DYAD | HTN | ARTHRITIS | | 1.98 | 1.89 | 2.38 | 1.91 | 1.73 | 1.26 | 1.82 |
| DYAD | OBESITY | DIABETES | | 1.92 | 1.98 | 1.80 | 1.66 | 1.58 | 1.68 | 1.81 |
| DYAD | HTN | CANCER | | 1.66 | 1.59 | 2.50 | 1.69 | 0.50 | 1.11 | 1.81 |
| DYAD | OBESITY | HTN | | 1.65 | 1.70 | 1.60 | 1.47 | 1.28 | 1.31 | 1.52 |
| DYAD | HEART | ASTHMA | | 1.55 | 1.39 | 1.68 | 1.72 | 0.45 | 1.41 | 1.65 |
| DYAD | ASTHMA | ARTHRITIS | | 1.53 | 1.42 | 1.68 | 1.55 | 1.85 | 1.43 | 1.60 |
| DYAD | OBESITY | LIVER | | 1.52 | 1.50 | 1.13 | 1.17 | 1.33 | 1.45 | 1.00 |
| DYAD | OBESITY | ARTHRITIS | | 1.50 | 1.50 | 1.55 | 1.41 | 1.12 | 1.27 | 1.31 |
| DYAD | DIABETES | ASTHMA | | 1.34 | 1.26 | 1.30 | 1.32 | 1.71 | 0.99 | 1.32 |
| DYAD | OBESITY | HEART | | 1.32 | 1.34 | 1.14 | 1.28 | 1.61 | 1.11 | 1.26 |
| DYAD | CANCER | ASTHMA | | 1.28 | 1.14 | 1.93 | 1.53 | 0.69 | 1.52 | 1.61 |
| DYAD | OBESITY | ASTHMA | | 1.26 | 1.24 | 1.28 | 1.27 | 1.21 | 1.19 | 1.13 |
| DYAD | HTN | ASTHMA | | 1.19 | 1.10 | 1.38 | 1.24 | 1.58 | 1.24 | 1.24 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| DYAD | OBESITY | CANCER | | 1.05 | 0.99 | 1.01 | 1.28 | 1.20 | 1.28 | 1.18 |
| | | | | | | | | | | |
| TRIAD | HTN | DIABETES | HEART | **9.91** | **9.51** | 9.17 | **7.74** | 2.04 | **5.02** | **9.10** |
| TRIAD | HTN | DIABETES | ARTHRITIS | 7.62 | 7.24 | 8.68 | 6.00 | 3.35 | 3.10 | 6.56 |
| TRIAD | HTN | HEART | ARTHRITIS | 6.72 | 5.84 | **10.27** | 6.03 | 4.39 | 2.36 | 6.87 |
| TRIAD | OBESITY | HTN | DIABETES | 6.02 | 6.45 | 6.20 | 4.30 | 2.77 | 2.90 | 5.18 |
| TRIAD | OBESITY | DIABETES | LIVER | 5.83 | 6.00 | 5.80 | 2.78 | 3.33 | 3.67 | 2.43 |
| TRIAD | OBESITY | DIABETES | ARTHRITIS | 5.27 | 5.15 | 6.38 | 4.05 | 1.98 | 3.18 | 4.59 |
| TRIAD | OBESITY | HTN | STROKE | 5.23 | 5.64 | 5.82 | 3.75 | 1.66 | 2.26 | 4.00 |
| TRIAD | HTN | CANCER | ARTHRITIS | 4.88 | 4.43 | 8.61 | 4.80 | 0.00 | 1.95 | 5.84 |
| TRIAD | HEART | ASTHMA | ARTHRITIS | 4.85 | 3.80 | 7.11 | 4.77 | 1.88 | 2.81 | 5.74 |
| TRIAD | OBESITY | HEART | ARTHRITIS | 3.99 | 3.67 | 5.14 | 3.47 | **5.06** | 1.96 | 3.89 |
| TRIAD | CANCER | ASTHMA | ARTHRITIS | 3.91 | 3.39 | 6.57 | 3.93 | 3.84 | 2.86 | 6.16 |
| TRIAD | OBESITY | HTN | HEART | 3.85 | 3.88 | 3.88 | 3.24 | 2.26 | 2.06 | 3.68 |
| TRIAD | OBESITY | HTN | ARTHRITIS | 3.77 | 3.77 | 4.52 | 3.08 | 2.18 | 1.94 | 2.99 |
| TRIAD | HTN | HEART | ASTHMA | 3.57 | 2.87 | 4.15 | 3.77 | 1.01 | 2.50 | 3.98 |
| TRIAD | HTN | ASTHMA | ARTHRITIS | 3.28 | 2.87 | 4.45 | 3.02 | 3.71 | 2.22 | 3.31 |
| TRIAD | OBESITY | CANCER | ARTHRITIS | 3.10 | 2.84 | 2.78 | 3.39 | 4.15 | 2.14 | 3.14 |
| TRIAD | OBESITY | DIABETES | ASTHMA | 3.02 | 2.95 | 2.78 | 2.50 | 3.18 | 1.56 | 2.65 |
| TRIAD | OBESITY | HTN | CANCER | 2.62 | 2.53 | 3.53 | 2.59 | 0.67 | 1.79 | 2.73 |
| TRIAD | OBESITY | ASTHMA | ARTHRITIS | 2.58 | 2.45 | 2.80 | 2.32 | 2.38 | 2.00 | 2.18 |
| TRIAD | OBESITY | HEART | ASTHMA | 2.45 | 2.34 | 2.18 | 2.28 | 0.40 | 2.09 | 2.19 |
| TRIAD | OBESITY | HTN | ASTHMA | 2.27 | 2.19 | 2.72 | 1.97 | 2.26 | 1.84 | 1.92 |

OER = observed-to-expected ratio; IHS = Indian Health Service; VHA = Veterans Health Administration; HTN = hypertension; **bold** = dyad and triad pattern with highest OER by payer group; the analysis was performed using Stata version 18 (College Station, TX).

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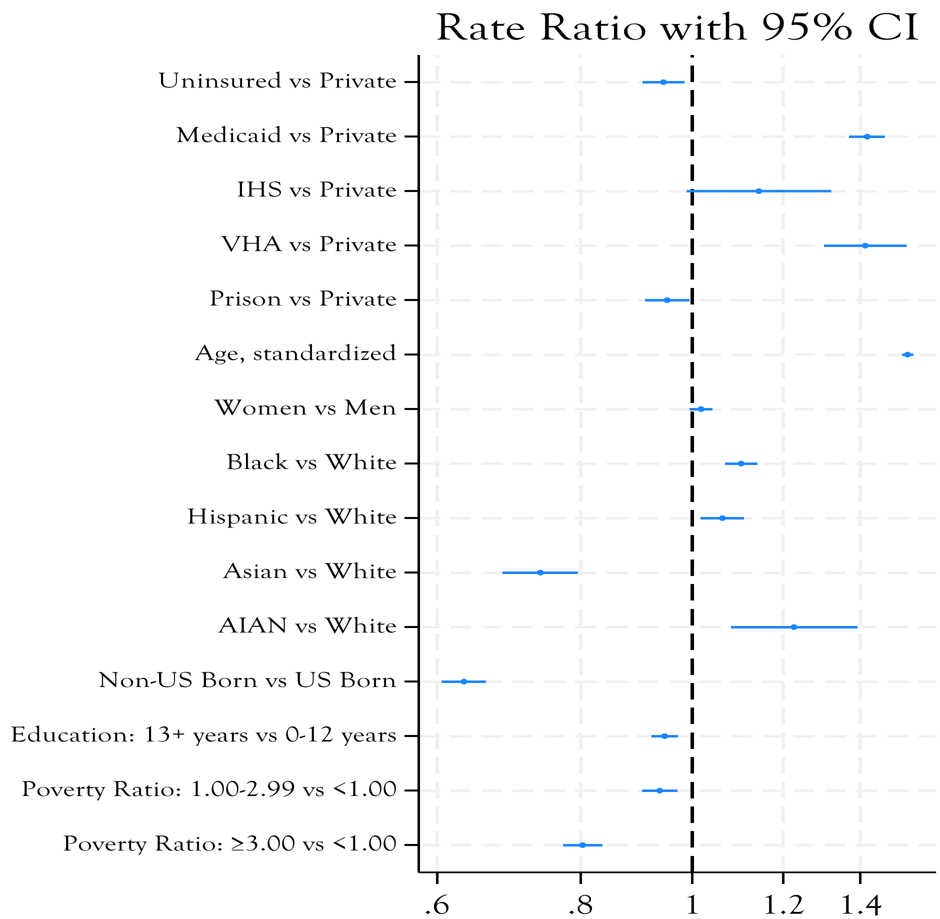
**Figure 1: Forest plot of negative binomial regression model of the number of chronic conditions, United States, 2016–2018**




IHS = Indian Health Service; VHA = Veterans Health Administration; AIAN = American Indian/Alaska Native; CI = confidence interval; age was standardized by centering the data to have a mean of zero and standard deviation of one; the analysis was performed using Stata version 18 (College Station, TX).

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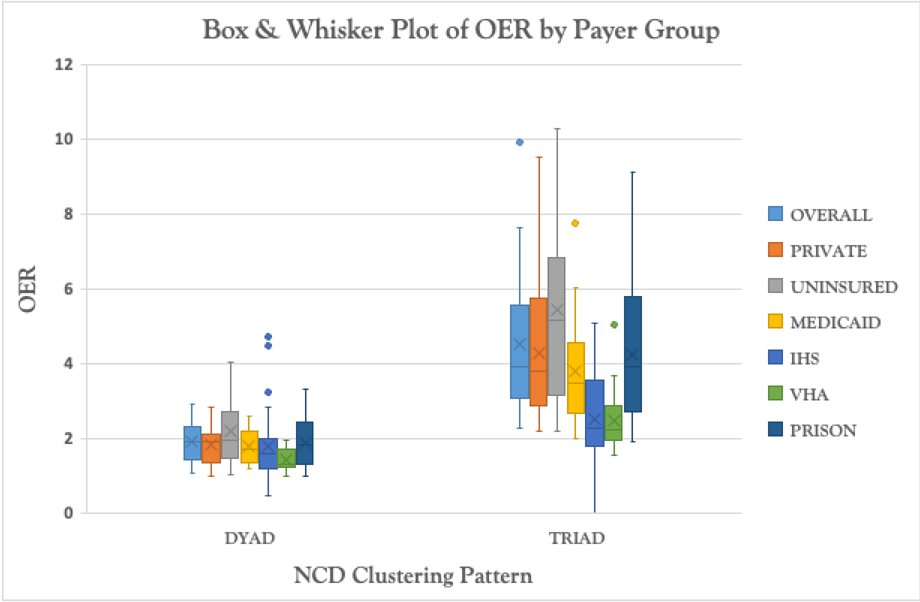
**Figure 2: Box & whisker plot of observed-to-expected ratio (OER) by payer group and noncommunicable disease (NCD) clustering pattern, United States, 2016–2018**




OER = observed-to-expected ratio; IHS = Indian Health Service; VHA = Veterans Health Administration; NCD = noncommunicable disease