Are HCC Risk Scores a Reliable Health Status Indicator Across Rural and Urban Areas?

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Hierarchical Condition Category (HCC) coding is a risk assessment tool developed by the Centers for Medicare & Medicaid Services (CMS) to estimate future health care costs. The reliability of HCC risk scores as a health status indicator has been questioned based on observed regional and geographic differences in coding practices and varied diagnosis frequencies, indicating claims data may not adequately capture underlying health risk. This study examines HCC scores among rural and urban Medicare fee-for-service (FFS) beneficiaries and analyzes which factors drive observed differences.

Background

The CMS HCC coding model was originally developed as a risk assessment model for the Medicare Advantage program to estimate future healthcare costs.[1] By incorporating factors like age, sex, Medicaid eligibility, residence type, and diagnoses into its calculations, the HCC coding model seeks to prevent health insurance plans and providers from selectively treating only healthier, lower-cost beneficiaries. Despite its broad use, including for Medicare Advantage (Medicare Part C), Medicare Part D, and the Medicare Shared Savings Program, the HCC coding model faces challenges in fully capturing patient health complexity.[2] This challenge is an important consideration, given that even the best risk adjusters account for only a small fraction of risk due to the inherent uncertainty and unpredictability of healthcare spending.[2]

The HCC coding model, which relies on the International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) codes to assign risk scores to patients, is an important tool for CMS to estimate future healthcare costs and health care resource utilization. HCC risk scores are influenced by various factors unrelated to actual health status, such as the number and type of claims per beneficiary and/or the number of diagnoses coded on each claim. These differences are particularly evident for urban beneficiaries, where HCC risk scores are often higher, potentially reflecting higher acuity or complexity, or better access to care.[3] Risk

Key Takeaways

- **HCC Geographic Variation:** Rural residents have higher mortality rates and more chronic conditions than urban residents, yet HCC scores for rural Medicare fee-for-service beneficiaries are consistently lower than for their urban counterparts, implying better overall health status for rural beneficiaries and lower healthcare costs.
- **HCC Limitations:** HCC scores, based on patients' demographics and claims data, may not fully capture rural beneficiaries' health complexities.
- **HCC Policy Considerations:** HCC scores inform healthcare payment models and resource allocation, potentially disadvantaging rural providers. Accurate health indicators are essential for resource allocation.

score differences could be misleading because scores may not accurately represent a patient's health status, but rather may reflect differences in how claims are coded or how often patients use health services.[4]

Prior to implementing the HCC coding model, CMS evaluated a number of risk adjustment methods, including the Ambulatory Care Group (ACG) algorithm, the chronic disease and disability payment system (CDPS), the clinically detailed risk information system for cost (CD-RISC) and clinical risk groups (CRG), among others.[5–8] The HCC coding model stood out for its clinical relevance and adaptability.[9] However, the shift to ICD-10-CM in 2015 created new challenges. This shift expanded diagnoses' granularity significantly, necessitating periodic reviews of the HCC framework to ensure its relevance in appropriately predicting healthcare payment, quality, and performance.

Initially, the HCC coding model mapped ICD-10-CM diagnoses to ICD-9-CM categories. The HCC coding model was later updated to align directly with ICD-10 categories in version 24. The version 24 HCC coding model, used in this analysis, is intended to enhance the model's accuracy in reflecting healthcare costs across different settings.[10]

Previous research conducted by the University of North Carolina Sheps Center for Health Services Research assessed HCC risk scores using 2014 data and an HCC coding model that utilized ICD-9 categories.[11,12] Their analysis revealed a potential underestimation of healthcare costs for rural beneficiaries compared to urban counterparts and a consistent pattern of lower HCC risk scores in rural areas, despite indications of poorer health in these populations.[12] Lower HCC risk scores are inconsistent with studies describing the health status of rural populations. For example, differences in mortality rates between rural and urban areas persist and do not indicate a healthier rural population as the HCC risk scores suggest.[13] Similarly, rural areas experience higher rates of chronic disease. [14]

This study uses 2019 and 2021 data, a period after the ICD-10-CM coding stabilized, to reassess differences in HCC scores by rurality. We employed the version 24 HCC coding model, which maps directly to ICD-10-CM codes, offering a more contemporary assessment of rural and urban healthcare cost differences. We analyzed four common chronic conditions to determine if there was variation between rural and urban beneficiaries' HCC scores. This approach aimed to better understand how rural and urban providers' coding practices may affect HCC scores.

Methods

The study used a cross-sectional design to investigate differences in HCC risk scores among rural and urban Medicare Fee-for-Service (FFS) beneficiaries for the calendar years 2019 and 2021. The primary data source was the CMS Research Identifiable Files (RIF) for FFS claims. Additional beneficiary demographic and clinical information was obtained from the Master Beneficiary Summary File (MBSF), with data on chronic conditions and inpatient stays pulled from specific segments within the MBSF. This analysis uses the 2013 Urban Influence Codes to classify rural and urban counties.[15] For this study, metropolitan counties (UIC codes 1-2) are considered urban and nonmetropolitan and noncore counties (UIC codes 3-12) are considered rural and are further specified in this study as large rural (UIC codes 3, 5,

8), small rural (UIC codes 4, 6-7, 9-10), and isolated rural (UIC codes 11-12). This additional categorization allows for a more precise examination of healthcare differences across levels of rurality, by considering factors like population density and metropolitan area influence. The Claims-Based Frailty Index (CFI) Score designed by Harvard University serves as an additional measure of health status.[16]

The study population was comprised of Medicare FFS beneficiaries, excluding those with one or more months of Medicare Advantage Part C coverage and those with End-Stage Renal Disease (ESRD). CMS uses the HCC coding model to calculate risk scores for beneficiaries who are not in dialysis, transplant, or post-graft status, with multiple segments including community, institutional, and new enrollee segments.[17] Beneficiaries with ESRD as the original reason for entitlement are more likely to undergo dialysis and/or receive transplants; thus, CMS fully phased in a separate HCC coding model for these beneficiaries in 2022.[18] Beneficiaries whose original reason for Medicare eligibility was age or disability status were assigned an HCC community risk score. We also reviewed dual eligibility status (Medicaid-Medicare) using the plurality of dual eligibility status months in a calendar year to determine dual status and used December's dual eligibility status for beneficiaries with 6 months dual eligibility status during the year. We assigned beneficiaries the 'institutional' HCC risk score if they had a nursing home stay of more than 90 days in the calendar year, nursing home days were calculated based on the Minimum Data Set (MDS) nursing home assessment data. Beneficiaries with less than 12 months of Part B enrollment were assigned the 'new beneficiary' risk score.[i] HCC risk scores for each beneficiary were calculated based on the HCC risk score software model version 24.[19]

The Medicare FFS claims data were merged with Area Health Resource File data to include county-level characteristics, including county-level provider rates. Provider rates refer to the ratio of healthcare professionals to the population in a county. We then categorized risk scores into four distinct ranges based on a statistical review of the data distribution, each representing different expected healthcare utilization and costs relative to the average Medicare beneficiary (Exhibit 1). These four ranges were specifically chosen to provide a clearer understanding of the variations in healthcare needs and expenditures among different beneficiary groups.

Exhibit 1: Four HCC Score Ranges and Relationship to Healthcare Costs

- Below 0.5 – Lowest costs
- 0.5 - <1.0 – Costs just below the average
- 1.0 – 1.5 – Average costs to slightly above
- > 1.5 – Notably higher costs compared to average

We initially conducted descriptive analyses to summarize demographic and enrollment variables. Next, we conducted bivariate analyses comparing HCC scores across selected chronic conditions – hypertension, diabetes, depression, and chronic obstructive pulmonary disease (COPD) – for beneficiaries living in rural and urban areas; beneficiaries with multiple chronic conditions were included in more than one category of stratified analyses. We selected these conditions due to their prevalence and the variability in care management and coding practices that might affect the beneficiaries' HCC scores. Stratified analyses were conducted to investigate HCC score differences within subpopulations, aiming to

[i] HCC score community score segments include Partial Dual Aged, Partial Dual Disabled, Full Dual Aged, Full Dual Disabled, Non-dual Aged, Non-dual Disabled. Additionally, there are HCC Institutional and New Enrollee segments.

identify variables that contributed to HCC score variations. Both chi-square tests and t-tests were used for statistical comparison in analyses.

Results

This section presents demographic information about the Medicare FFS beneficiaries included in this study who had at least one of the four selected chronic conditions: hypertension, diabetes, depression, or COPD. We then show differences in Hierarchical Condition Category (HCC) scores among rural and urban Medicare FFS beneficiaries, and explore the influence of other variables, such as demographic factors and county-level variables, on HCC scores. This study provides a comprehensive review of the factors associated with HCC risk scores in rural and urban Medicare FFS populations.

Characteristics of the Medicare FFS Study Population

The Medicare FFS beneficiaries included in the study were diagnosed with least one of four chronic conditions: Chronic Obstructive Pulmonary Disease (COPD) (n=7,105,436), hypertension (n=24,133,674), diabetes (n=11,196,742), and depression (n=11,585,415). We then stratified the beneficiaries by rural (large rural, small rural, and isolated rural) and urban location as shown in Appendix Table A.1.

Overall, the Medicare FFS beneficiaries in the four chronic condition categories had an average age of 74 years; beneficiaries with a depression diagnosis tended to be younger with an average age of 72 years. Over half of the beneficiaries were female. Approximately one-quarter of beneficiaries also had Medicaid coverage (either part Medicaid or fully dual eligible). Healthcare utilization variables showed that nearly 79 percent did not have an inpatient stay. When comparing the Claims-Based Frailty Index (CFI) Score across the four selected chronic conditions, beneficiaries with COPD (0.20) had the highest score, and those with hypertension (0.17) had the lowest score.

Primary care and mental health provider rates were similar for the four chronic conditions but showed geographic variance; urban areas had the highest rate, while large rural areas had the lowest. It is worth noting that residents of rural areas might have a higher prevalence of high-risk occupations, such as farming and energy extraction, which could contribute to observed differences.[20] Appendix Table A.2 shows detailed demographic results that include age, sex, dual eligibility status, number of inpatient stays, CFI Score (frailty), and county-level provider rates in the beneficiary's county for primary care providers and mental health care providers for each analyzed condition.

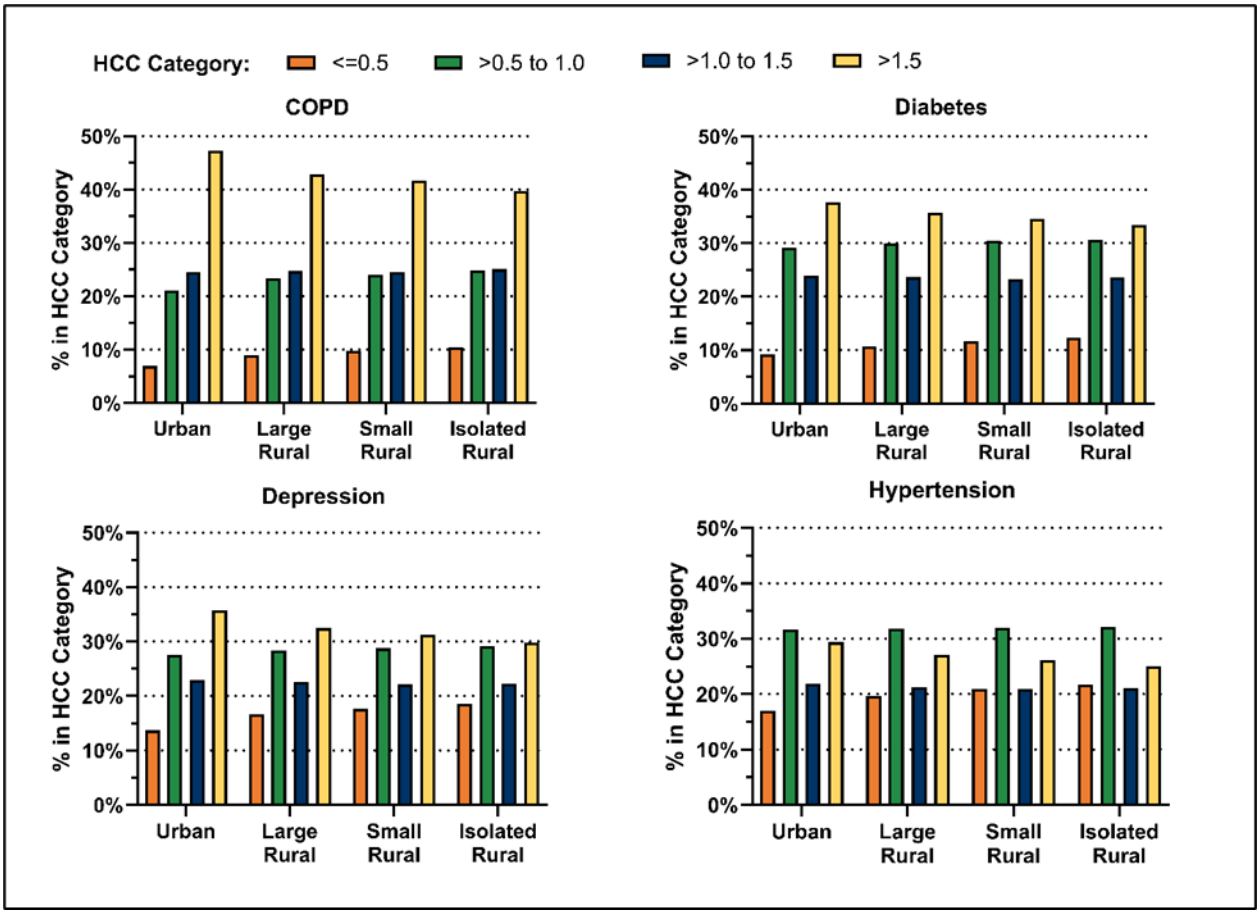
Geographic Variation in HCC Scores for Medicare FFS Beneficiaries with Four Chronic Conditions

Clear patterns emerged in the distribution of HCC scores when examining Medicare FFS beneficiaries by geographic classification: urban, large rural, small rural, and isolated rural (Exhibit 2).

A consistent trend across all four conditions was observed – the proportion of beneficiaries with high HCC scores (> 1.5) was highest for beneficiaries residing in urban areas and lowest for those beneficiaries residing in the most sparsely populated areas. Conversely, the proportion of beneficiaries with low HCC scores (≤0.5) was most prevalent in isolated rural areas and least prevalent in urban areas. There was minimal variation in the proportion of beneficiaries with moderate HCC scores, ranging from 0.5 to 1.0

and >1.0 to 1.5, across the urban to isolated rural continuum. This distribution suggests that factors other than geographic location might be influencing these mid-range scores.

Exhibit 2: Percentage of Medicare FFS Beneficiaries in HCC Categories by Rural Status for Four Chronic Conditions, 2019-2020



Medicare FFS beneficiaries diagnosed with COPD had the highest prevalence of elevated HCC scores, with percentages ranging from 40 percent to 47 percent with HCC scores greater than 1.5 across all geographical categories, as compared to the population of beneficiaries without COPD. The large percentage of beneficiaries with COPD who have high HCC scores is indicative of the considerable health care use and costs associated with COPD diagnosis for both urban and rural beneficiaries. Conversely, beneficiaries with hypertension were found to have the lowest percentage of high HCC scores (scores > 1.5) among the four chronic condition groups, ranging between 25 percent and 30 percent, across the different levels of rurality.

Urban areas appear to have less healthy Medicare beneficiaries than rural areas -- the highest HCC score category (least healthy, most costly) consistently includes a higher percentage of beneficiaries in urban areas than in rural areas across all four chronic conditions. Conversely, the HCC scores indicate that as population density decreases (i.e., from urban to large rural to small rural to isolated rural), the level of health improves, and the expected healthcare costs decline. Yet, for the past 30 years, mortality rates

have been highest in the most sparsely populated areas and lowest in urban areas indicating that rural residents do not experience better health than their urban counterparts.[13,21]

Conclusions

This study examined differences in Hierarchical Condition Category (HCC) risk scores among rural and urban Medicare Fee-for-Service (FFS) beneficiaries across four common conditions: COPD, hypertension, diabetes, and depression. Our findings do not align with recent studies of differences in rural/urban health status and mortality, indicating that the HCC coding model may still underrepresent the health complexities and associated costs of rural populations. Urban beneficiaries generally had higher HCC risk scores compared to their rural counterparts, a trend that is especially prominent among those diagnosed with COPD. This trend persisted following the transition from ICD-9-CM to ICD-10-CM.

Our findings highlight a difference between HCC risk scores and national public health indicators reported by the Centers for Disease Control and Prevention (CDC). CDC data consistently shows worse health outcomes among rural residents compared to urban populations.[22] For example, rural areas have higher morbidity, mortality rates, and poorer self-rated health status compared to urban counterparts, driven significantly by chronic diseases such as COPD, hypertension, and diabetes.[22,23]

HCC risk scores are widely used as a means of quantifying the expected costs of patients' care. These risk scores are important because they inform resource allocation, assist in risk adjustment, and contribute to the understanding of the health complexities within specific patient populations. However, while HCC risk scores can be informative, they are not without limitations—most notably, they do not capture degrees of patient acuity. For example, HCC risk scores tend to be higher in urban settings, as observed in this study, which could be interpreted as indicative of higher patient acuity or complexity. However, this interpretation may be misleading, because HCC risk scores can also be affected by factors unrelated to the patient's actual health severity, such as 'coding intensity' – the number and type of claims per beneficiary or the quantity of diagnosis codes within each claim – or access to care.[24]

Coding intensity refers to the practice of systematically increasing the number and specificity of diagnoses recorded on healthcare claims to enhance the accuracy of patient risk scores.[25] While coding intensity can lead to better resource allocation and improved care management, it also creates incentives for providers to document more diagnoses, which can inflate risk scores. Likewise, these differences may be reflective of health service availability, particularly specialist care. The Medicare Payment Advisory Commission found that rural beneficiaries had fewer evaluation and management encounters in 2018 than urban beneficiaries; these differences were attributed to fewer visits with specialist physicians.[26] Fewer specialist visits and the associated coding may be reflected in HCC scores.

Given these limitations, there is a pressing need to identify more appropriate indicators that can accurately reflect the health status of both urban and rural Medicare beneficiaries. While HCC risk scores serve as a useful starting point, relying solely on them could exacerbate resource gaps and misrepresent actual patient needs. Future research could assess more comprehensive metrics, such as claims based frailty indices to describe healthcare complexities. This level of precision is essential for developing policies and interventions that meet the needs of diverse beneficiary populations, thereby enhancing the efficacy of healthcare systems.

Based on the study findings, policy considerations may include the identification or development and validation of health status indicators that go beyond the scope of current HCC scores. These indicators could be designed to capture a more nuanced picture of patient health, particularly in areas where HCC scores may not fully account for differences in access and care needs by rurality. For example, the incorporation of claims-based frailty indices could offer a more accurate representation of patient acuity, especially in diverse health care settings. Furthermore, understanding the impact of varying medical coding practices between urban and rural care providers is crucial. Investigating these gaps may inform adjustments in the HCC coding model, ensuring that it more accurately represents health status across different geographies.

Limitations

This study has limitations that may impact generalizability. Given the cross-sectional nature, we can identify associations but not causality. The adoption of ICD-10-CM, which occurred after the development of the HCC coding model, brings forth potential distinctions in coding that might impact HCC risk score accuracy. Our geographical classifications, while detailed, may still overlook certain complexities of rural and urban distinctions. Emphasizing specific chronic conditions, like hypertension and diabetes, might omit other impactful conditions. The reliance on claims data, which may not always align with actual clinical scenarios, coupled with potential regional coding variations, could influence derived HCC risk scores. Lastly, our focus on the 2019 to 2021 calendar years may not reflect evolving healthcare practices in subsequent years.

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Appendix

Table A.1: Beneficiary Characteristics by Chronic Condition Diagnosis and Rurality

	Urban		Large Rural		Small Rural		Isolated Rural	
	N (mean)	% (SD)	N (mean)	% (SD)	N (mean)	% (SD)	N (mean)	% (SD)
COPD	**5,433,284**		**1,050,974**		**496,073**		**125,105**	
Age	(75.72)	(11.02)	(74.25)	(11.09)	(74.21)	(11.14)	(74.32)	(11.11)
Sex								
Male	2,387,794	44.0	485,860	46.2	229,691	46.3	59,907	47.9
Female	3,045,490	56.1	565,114	53.8	266,382	53.7	65,198	52.1
Dual Status								
Full	1,147,415	21.1	215,932	20.6	103,840	20.9	28,367	22.7
None	4,020,246	74.0	750,881	71.5	348,928	70.3	85,701	68.5
Partial	265,623	4.9	84,161	8.0	43,305	8.7	11,037	8.8
Inpatient Stays								
0	3,893,785	71.7	773,800	73.6	369,286	74.4	93,573	74.8
1	952,482	17.5	179,539	17.1	83,468	16.8	20,744	16.6
2+	587,017	10.8	97,635	9.3	43,319	8.7	10,788	8.6
Frailty Score	(0.20)	(0.08)	(0.20)	(0.07)	(0.20)	(0.07)	(0.20)	(0.07)
MH Prov Rate	(174.1)	(114.5)	(85.96)	(81.45)	(117.4)	(116.7)	(139.5)	(265.2)
Phys Prov Rate	(6.89)	(7.94)	(0.88)	(1.94)	(1.64)	(4.41)	(0.94)	(2.21)
Diabetes	**8,998,154**		**1,406,148**		**638,818**		**153,622**	
Age	(74.46)	(10.57)	(73.31)	(10.55)	(73.14)	(10.56)	(73.33)	(10.51)
Sex								
Male	4,288,199	47.7	695,571	49.5	315,304	49.4	77,600	50.5
Female	4,709,955	52.3	710,577	50.5	323,514	50.6	76,022	49.5
Dual Status								
Full	1,805,630	20.1	238,516	17.0	111,250	17.4	28,236	18.4
None	6,836,034	76.0	1,077,696	76.6	480,698	75.3	114,106	74.3
Partial	356,490	4.0	89,937	6.4	46,870	7.3	11,280	7.3
Inpatient Stays								
0	7,034,058	78.2	1,103,985	78.5	506,183	79.2	121,660	79.2
1	1,270,060	14.1	200,819	14.3	89,566	14.0	21,510	14.0
2+	694,036	7.7	101,345	7.2	43,069	6.7	10,452	6.8
Frailty Score	(0.19)	(0.07)	(0.19)	(0.07)	(0.19)	(0.07)	(0.19)	(0.07)
MH Prov Rate	(179.2)	(115.0)	(85.57)	(81.63)	(118.0)	(116.4)	(127.9)	(238.7)
Phys Prov Rate	(7.38)	(8.15)	(0.90)	(2.00)	(1.66)	(4.46)	(0.91)	(2.12)
Depression	**9,132,555**		**1,553,278**		**724,821**		**174,761**	
Age	(71.92)	(13.29)	(70.66)	(13.34)	(70.67)	(13.26)	(70.90)	(13.16)
Sex								
Male	3,218,768	35.2	558,330	36.0	259,430	35.8	64,630	37.0
Female	5,913,787	64.8	994,948	64.1	465,391	64.2	110,131	63.0
Dual Status								
Full	2,111,339	23.1	356,507	23.0	165,108	22.8	42,540	24.3

None	6,574,287	72.0	1,078,469	69.4	498,924	68.8	117,777	67.4
Partial	446,929	4.9	118,302	7.6	60,789	8.4	14,444	8.3
Inpatient Stays								
0	7,141,202	78.2	1,237,141	79.7	581,552	80.2	140,707	80.5
1	1,280,817	14.0	211,458	13.6	97,201	13.4	23,027	13.2
2+	710,536	7.8	104,679	6.7	46,068	6.4	11,027	6.3
Frailty Score	(0.19)	(0.07)	(0.19)	(0.07)	(0.19)	(0.07)	(0.19)	(0.07)
MH Prov Rate	(184.8)	(120.2)	(89.93)	(84.19)	(122.7)	(114.9)	(129.6)	(229.6)
Phys Prov Rate	(7.31)	(8.54)	(0.92)	(2.02)	(1.80)	(4.78)	(0.94)	(2.16)
Hypertension	**19,096,988**		**3,187,854**		**1,482,715**		**366,117**	
Age	(74.64)	(10.22)	(73.79)	(10.35)	(73.76)	(10.38)	(74.04)	(10.29)
Sex								
Male	8,713,957	45.6	1,497,138	47.0	694,721	46.9	176,220	48.1
Female	10,383,031	54.4	1,690,716	53.0	787,994	53.2	189,897	51.9
Dual Status								
Full	2,828,847	14.8	422,629	13.3	199,098	13.4	52,638	14.4
None	15,617,080	81.8	2,587,555	81.2	1,191,045	80.3	291,182	79.5
Partial	651,062	3.4	177,671	5.6	92,572	6.2	22,297	6.1
Inpatient Stays								
0	5,573,426	81.6	2,621,636	82.2	1,226,803	82.7	302,375	82.6
1	2,408,402	12.6	397,611	12.5	181,985	12.3	45,196	12.3
2+	1,115,161	5.8	168,608	5.3	73,927	5.0	18,546	5.1
Frailty Score	(0.17)	(0.07)	(0.17)	(0.06)	(0.17)	(0.06)	(0.17)	(0.06)
MH Prov Rate	(179.5)	(116.6)	(86.64)	(82.12)	(118.7)	(113.7)	(126.8)	(247.4)
Phys Prov Rate	(7.19)	(8.21)	(0.90)	(2.00)	(1.70)	(4.59)	(0.91)	(2.16)

Table A.2: Unadjusted and Adjusted Average HCC Scores by Chronic Condition Diagnosis and Rurality

Chronic Condition Diagnosis	N	Mean	Standard Error
COPD			
Urban	5,433,284	2.056	0.001
Large Rural	1,050,974	1.871	0.002
Small Rural	496,073	1.820	0.002
Isolated Rural	125,105	1.743	0.004
Diabetes			
Urban	8,998,154	1.743	0.001
Large Rural	1,406,149	1.658	0.001
Small Rural	638,818	1.616	0.002
Isolated Rural	153,622	1.567	0.004
Depression			
Urban	9,132,555	1.668	0.001
Large Rural	1,553,278	1.537	0.001
Small Rural	724,821	1.494	0.002

Isolated Rural	174,761	1.440	0.003
Hypertension			
Urban	19,096,989	1.452	0.000
Large Rural	3,187,855	1.363	0.001
Small Rural	1,482,715	1.328	0.001
Isolated Rural	366,117	1.287	0.002