

Does Medical Insurance Coverage Translate Into Professional Care Seeking After Illness? Temporal Heterogeneity and Within-Person Evidence From the China Health and Nutrition Survey, 2004-2015

Yongji Zheng

Jinzhou Medical University

Jing Wang

15154462369@163.com

Jinzhou Medical University

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Abstract

Background

Rapid expansion of health-insurance enrollment does not necessarily imply that people seek professional care when illness occurs. We examined whether the insured-versus-uninsured association with professional care seeking was stable across a period of major insurance expansion and whether the population-average estimate was supported by within-person evidence.

Methods

Eligible CHNS illness person-waves came from 2004, 2006, 2009, 2011 and 2015. Professional care seeking was defined from M26B and current insurance from M1. Population-average logistic GEE adjusted for age, sex, residence, education, illness severity and wave. Robustness analyses tested insurance-by-wave interaction, estimated wave-specific associations, excluded 2015 because uninsured observations were sparse, restricted to repeated illness records, and used conditional logistic regression among people whose insurance and care-seeking status both changed.

Results

The main analysis included 7,982 illness person-waves from 6,254 individuals. The pooled association was null (OR = 1.027, 95% CI 0.895–1.178; $P = 0.705$), but insurance-by-wave heterogeneity was present (global interaction $P = 0.0037$). Wave-specific adjusted ORs were 0.959 in 2004, 0.898 in 2006, 1.249 in 2009, 1.954 (95% CI 1.294–2.949) in 2011 and 1.283 in 2015. Only 32 uninsured illness observations remained in 2015. Excluding 2015 left the pooled estimate essentially unchanged (OR = 1.022, 95% CI 0.888–1.175). The within-person estimate was OR = 1.546 (0.896–2.667) and was imprecise because only 216 exposure/outcome switchers contributed.

Conclusions

A single pooled insurance coefficient concealed substantial temporal heterogeneity and weakening exposure overlap as coverage approached universality. The results do not identify a stable causal insurance effect; instead, they show why enrollment, policy period, overlap and realized service use should be separated when evaluating healthcare access.

1 Background

Using CHNS illness episodes from 2004, 2006, 2009, 2011 and 2015, we evaluated the association between current insurance coverage and professional care seeking after illness or injury. The primary analysis used population-average generalized estimating equations, while sensitivity analyses evaluated

repeated-observation participants, within-person contrasts, survey-wave heterogeneity and sparse uninsured observations in later waves. We prespecified that results would be interpreted as observational associations rather than causal effects of insurance and that a binary coverage variable would not be equated with benefit generosity.

A further challenge is that China's insurance environment changed markedly between 2004 and 2015. Pooling all survey years into one insured-versus-uninsured coefficient assumes that the association is stable despite policy expansion and shrinking numbers of uninsured respondents. Later waves may also suffer from limited exposure overlap, making an average effect difficult to interpret. Repeated observations provide an opportunity to separate a population-average association from within-person change, but the latter is identified only by people whose insurance status and care-seeking behavior both vary.

Health-service use is shaped by predisposing characteristics, enabling resources and perceived or evaluated need, as summarized by Andersen's behavioral model [9]. Insurance can reduce direct price barriers, but illness severity, household resources, distance, perceived quality, migration status and local provider supply may modify whether an insured person actually seeks professional care. Empirical studies have reported heterogeneous relationships between insurance and preventive, outpatient and hospital use [4–8, 12, 13, 18–21, 28].

Universal health coverage involves enrollment in an insurance program and timely use of appropriate services when health needs arise. China expanded social health insurance rapidly during the 2000s and 2010s, yet the depth of benefits, reimbursement arrangements, provider networks and patient cost sharing differed across schemes and periods [14–24]. A binary indicator of coverage can represent nominal entitlement without fully capturing financial protection or realized access.

This distinction matters for health-services research because enrollment, financial protection and realized utilization are separate outcomes. Insurance may affect whether care is affordable without fully determining whether an ill person seeks professional care, which also depends on symptom severity, perceived quality, distance, provider supply, household resources and opportunity costs [9, 14–24]. We treated wave heterogeneity and positivity as central components of the analysis rather than as optional post hoc subgroup exploration.

The 2004–2015 period is analytically important because China's health-insurance landscape changed rapidly. Expansion of the New Cooperative Medical Scheme, urban resident coverage and subsequent movement toward broader universal coverage substantially reduced the proportion of uninsured people, while benefit depth, reimbursement rules and local implementation continued to differ [14–24]. The meaning of an "insured" indicator was not constant across calendar time. A pooled association can be useful as a descriptive average, but it can also conceal policy-period heterogeneity and weak exposure overlap in later years.

Rather than estimating the effect of a single insurance scheme, this analysis tests whether a simple binary coverage contrast retains a stable meaning across five survey waves as the uninsured comparison group collapses, and whether repeated-observation and within-person analyses support the population-average result.

2 Methods

2.1 Study design, setting and data structure

This study was a repeated-measures secondary analysis of individual CHNS data from 2004, 2006, 2009, 2011 and 2015 [1, 2]. The unit of analysis was an eligible illness person-wave rather than an individual at enrollment. CHNS follows individuals and households in selected communities; it is not a nationally representative probability sample. Person-wave records were linked by IDIND, and within-person correlation was retained rather than collapsing repeated illness observations to one record per participant. Reporting was guided by STROBE [3].

2.2 Eligibility and construction of illness episodes

A person-wave was eligible when M23 = 1 indicated illness or injury during the previous four weeks, M26B contained one of the four prespecified responses describing how the episode was handled, and insurance status M1 was coded 0 or 1. This restriction focused the analysis on observations in which a recent health need was reported. It does not estimate healthcare use in the entire CHNS population and should not be interpreted as a general annual utilization rate. Records lacking the adjustment variables required by a model were excluded from that model.

2.3 Exposure: medical-insurance coverage

Current medical-insurance coverage was defined from M1 as insured (1) versus uninsured (0). CHNS contains additional insurance-type fields in some waves, but availability and coding were not sufficiently consistent across all five waves for a harmonized scheme-specific longitudinal exposure. We retained the binary M1 indicator as the primary exposure and explicitly treated it as a measure of enrollment, not reimbursement generosity, actuarial value or effective financial protection. Scheme-type field availability was reviewed descriptively to support this limitation.

2.4 Outcome: professional care seeking

The binary outcome was derived from M26B. Professional care seeking was coded 1 when the respondent reported consulting a local health worker (M26B = 2) or doctor (M26B = 3), and 0 for self-care (M26B = 1) or ignoring/no care (M26B = 4). This operational definition captures whether a professional provider was contacted after a recent illness episode. It is a study-derived binary outcome and is not a validated scale of access, appropriateness or quality of care.

2.5 Covariates and temporal coding

Age (AGE), residence (T2; urban = 1), education (A12; valid categories 0–6), illness severity (M25) and survey wave were treated as time-specific. Sex was obtained from the master file. The covariates were selected a priori to capture demographic predisposition, enabling context and illness need. Wave indicators were included to absorb broad secular changes in insurance expansion and health-service organization. Because age and calendar wave are nearly deterministic within an individual, the within-person conditional analysis omitted age when wave was included to reduce instability from collinearity.

2.6 Cross-wave variable harmonization

Variable definitions were harmonized before records were stacked across waves. Only codes with the same substantive interpretation in the selected surveys were retained in the pooled exposure and outcome definitions. Insurance was intentionally reduced to the stable M1 enrolled/not-enrolled contrast because more detailed scheme fields were not consistently comparable across all five waves. Education codes outside the documented 0–6 range and illness-response codes outside the prespecified categories were treated as missing rather than recoded by assumption. This harmonization strategy favors comparability over finer but wave-specific exposure detail.

2.7 Primary population-average model

The primary analysis used a binomial generalized estimating equation with logit link, IDIND clustering and an exchangeable working correlation structure [10, 25–27]. The model included insurance, age, sex, urban residence, education, illness severity and categorical wave. Odds ratios with robust 95% confidence intervals were reported. GEE was selected because the research question concerned the average association across eligible illness episodes while accounting for correlation of repeated observations from the same person; the coefficient should not be interpreted as an individual-specific causal effect. [11]

2.8 Correlation structure, interaction testing and precision

The exchangeable GEE working correlation assumed a common within-person correlation among eligible illness observations; robust sandwich standard errors protect coefficient inference against misspecification of that working correlation [10, 29, 30, 32]. For the insurance-by-wave model, wave was represented categorically and all interaction terms were tested jointly with a Wald test before wave-specific estimates were interpreted. We did not select individual waves according to nominal significance. Numbers of insured and uninsured illness episodes were examined in each wave as a practical overlap diagnostic, because a model can be numerically estimable even when one exposure group becomes too sparse for stable interpretation.

2.9 Temporal heterogeneity and overlap

To test whether the insured-versus-uninsured association was stable over time, an insurance-by-wave interaction was added to the GEE and the interaction coefficients were assessed jointly with a Wald test. Wave-specific adjusted logistic models using the same core covariates were then fitted to describe the direction and precision of contrasts within each survey year. Exposure overlap was summarized as

insured and uninsured counts by wave. Because only 32 eligible uninsured illness observations remained in 2015, a sensitivity analysis repeated the pooled GEE after omitting 2015. This strategy was used to flag, rather than conceal, the positivity limitation created by near-universal later-wave coverage.

2.10 Repeated-observation and within-person sensitivity analyses

A first sensitivity analysis restricted the GEE to participants contributing at least two eligible illness person-waves. A second analysis used conditional logistic regression among participants with at least two eligible observations and variation in both insurance status and the care-seeking outcome. This estimator conditions out stable person-level characteristics but necessarily discards non-switchers; the resulting estimate pertains to a selected group of insurance and outcome switchers rather than to the entire cohort. Time-varying illness severity and survey wave were included in this model.

2.11 Sensitivity-model estimands

The three analyses answer different questions. The primary GEE estimates a population-average association across eligible illness episodes. Restricting to people with repeated eligible episodes evaluates whether findings are driven by one-time contributors. Conditional logistic regression estimates an association identified only by within-person changes in both insurance and care seeking, thereby controlling stable personal characteristics but changing the target population to switchers. These estimands were not expected to be numerically identical, and discordance was interpreted in relation to precision and selection rather than used to choose the most favorable result [31, 34, 35]

2.12 Missing data, information size and statistical interpretation

No imputation was applied to the principal exposure, outcome or model covariates because the analysis was episode-based and the central concern was transparent comparability of observed coding across waves. The database fixed the available sample size. Accordingly, no retrospective power calculation was used. We report the numbers of person-waves, unique persons and switchers for each model and interpret uncertainty from confidence intervals. The very small uninsured sample in 2015 and the 216 switchers contributing to the conditional analysis were treated as limitations on precision and transportability rather than as reasons to search for alternative significance thresholds. [33]

2.13 Software and reproducibility

Data processing and statistical analyses were conducted in Python 3.13.5 with pandas 2.2.3, NumPy 2.3.5 and statsmodels 0.14.6. Eligibility rules, recoding, GEE models, interaction testing and conditional logistic regression were implemented in reproducible scripts. Two-sided P values and 95% confidence intervals are reported, but interpretation centers on consistency across designs, temporal heterogeneity and practical meaning rather than statistical significance alone.

3 Results

3.1 Sample

The complete primary analysis contained 7,982 eligible illness person-waves from 6,254 individuals. Across these observations, mean age was 53.31 years, 55.9% were female, 43.6% were urban residents, 74.5% were insured, and 65.4% involved professional care seeking after the reported illness or injury (Table 1). Because the unit of analysis was the illness person-wave, some participants contributed more than one observation. Insurance coverage increased substantially across the 2004–2015 survey period, whereas crude professional care-seeking rates varied across waves and insurance groups. These descriptive time trends establish the changing policy context but do not isolate an insurance effect because age, severity, residence, education, and other characteristics also changed across observations. Figure 1 shows how the recent-illness definition and complete-case requirements reduced the broader CHNS sample to the analytic person-waves.

Table 1
Characteristics of eligible illness person-waves.

Characteristic	Person-waves (N = 7,982)
Age, years	53.31 (18.29)
Female sex	4463 (55.9%)
Urban residence	3482 (43.6%)
Insured	5950 (74.5%)
Formal care seeking	5224 (65.4%)
Illness severity M25 = 1	2805 (35.1%)
Illness severity M25 = 2	4180 (52.4%)
Illness severity M25 = 3	997 (12.5%)
Wave 2004	1683 (21.1%)
Wave 2006	1349 (16.9%)
Wave 2009	1591 (19.9%)
Wave 2011	2298 (28.8%)
Wave 2015	1061 (13.3%)
Education A12 = 0	2270 (28.4%)
Education A12 = 1	1707 (21.4%)
Education A12 = 2	2094 (26.2%)
Education A12 = 3	928 (11.6%)
Education A12 = 4	419 (5.2%)
Education A12 = 5	547 (6.9%)
Education A12 = 6	17 (0.2%)

Values are mean (SD) or n (%). Percentages are based on person-wave observations.

3.2 Primary and sensitivity analyses

In the population-average GEE, insurance coverage was not associated with professional care seeking after adjustment for age, sex, residence, education, illness severity, and wave (OR = 1.027, 95% CI 0.895–1.178; P = 0.705). Restricting the analysis to 3,082 observations from 1,354 participants with at least two eligible illness records produced OR = 0.876 (95% CI 0.708–1.085; P = 0.226). The stricter within-person conditional logistic analysis was limited to 553 observations from 216 individuals whose insurance and

care-seeking status both varied and yielded OR = 1.546 (95% CI 0.896–2.667; P = 0.118) (Table 2; Fig. 2). Although the point estimates differed in direction, none excluded the null, and the conditional estimate was much less precise because it was identified only by a small group of exposure and outcome switchers.

Table 2
Association between insurance coverage and professional care seeking.

Analysis	Person-waves	Persons	OR	95% CI	P value
Main population-average GEE	7982	6254	1.027	0.895–1.178	0.705
Sensitivity: persons with ≥ 2 eligible observations	3082	1354	0.876	0.708–1.085	0.226
Within-person conditional logistic regression	553	216	1.546	0.896–2.667	0.118

ORs compare insured with uninsured observations. Main GEE adjusted for age, sex, residence, education, illness severity and wave; the within-person conditional model adjusted for time-varying severity and wave.

3.3 Interpretation of heterogeneity

The contrast between the population-average and within-person estimates should be interpreted as design-related heterogeneity rather than evidence that one model reveals a hidden beneficial or adverse effect. GEE uses both between-person and within-person information and estimates an average association across eligible illness episodes. Conditional logistic regression removes time-invariant person-level factors but discards individuals without relevant within-person changes. In this dataset, that restriction reduced the effective sample from 6,254 people to 216 switchers. The resulting confidence interval was correspondingly wide and overlapped both modest benefit and no association. Table 3 further shows that crude care-seeking rates changed across survey waves, underscoring the need to separate secular changes in China's health system from the effect of a binary insurance indicator.

Table 3
Crude professional care-seeking rates by wave and insurance status.

Wave	Insurance status	Person-waves	Professional care-seeking rate
2004	Uninsured	1116	0.639
2004	Insured	567	0.556
2006	Uninsured	624	0.692
2006	Insured	725	0.646
2009	Uninsured	154	0.623
2009	Insured	1437	0.683
2011	Uninsured	106	0.519
2011	Insured	2192	0.691
2015	Uninsured	32	0.500
2015	Insured	1029	0.616

Rates are descriptive and unadjusted; they should not be interpreted as causal effects of insurance.

3.4 Temporal heterogeneity and overlap

The insured-versus-uninsured association varied across survey waves (global insurance-by-wave interaction $P = 0.0037$). Adjusted ORs were 0.959 (95% CI 0.764–1.204) in 2004, 0.898 (0.703–1.148) in 2006, 1.249 (0.878–1.778) in 2009, 1.954 (1.294–2.949) in 2011, and 1.283 (0.606–2.718) in 2015 (Table 4; Fig. 3). Uninsured illness observations fell from 1,116 in 2004 to 106 in 2011 and 32 in 2015. Excluding 2015 left the pooled estimate essentially unchanged (OR = 1.022, 95% CI 0.888–1.175; $P = 0.765$). The within-person estimate was OR = 1.546 (95% CI 0.896–2.667), with wide uncertainty because only 216 switchers contributed. A single period-averaged coefficient did not describe all five survey waves adequately.

Table 4
Wave-specific adjusted associations between insurance and professional care seeking.

Wave	N	Uninsured	Insured	Adjusted OR	95% CI	P value
2004	1683	1116	567	0.959	0.764–1.204	0.718
2006	1349	624	725	0.898	0.703–1.148	0.392
2009	1591	154	1437	1.249	0.878–1.778	0.216
2011	2298	106	2192	1.954	1.294–2.949	0.001
2015	1061	32	1029	1.283	0.606–2.718	0.515

Wave-specific models used the same core covariates except the wave term. The global insurance-by-wave interaction test was $P = 0.0037$. Sparse uninsured observations in later waves limit precision and positivity.

4 Discussion

Medical-insurance coverage was not associated with professional care seeking in the pooled GEE, but the association differed across survey waves. The 2011 estimate was positive, whereas the estimates for 2004, 2006, 2009 and 2015 included the null or were imprecise. Because insurance arrangements, reimbursement, service supply and the composition of insured and uninsured groups changed over the same period, the 2011 estimate is best read as a period-specific association rather than a causal effect of insurance.

The result is consistent with the distinction between nominal coverage and effective access. Andersen's behavioral model treats service use as a function of predisposing characteristics, enabling resources and need, rather than insurance status alone [9]. The CHNS M1 indicator identifies whether insurance was present but does not capture scheme type, reimbursement rate, deductibles, portability, provider restrictions or out-of-pocket burden. Two people recorded as insured may face very different barriers to care.

Earlier evaluations of China's insurance expansion reported mixed effects on service use and financial protection, with results varying by scheme, service type and period [18–24]. The present estimates are not directly comparable with a policy evaluation of one scheme because the pooled M1 variable spans several insurance arrangements and reform phases. The wave-specific analysis shows that the insured-versus-uninsured contrast itself changed over time, which helps explain why studies using different periods or service outcomes may reach different conclusions.

The population-average and within-person estimates answer different questions. GEE used almost 8,000 illness person-waves and combined between-person and within-person information. The conditional model relied only on 216 people whose insurance and care-seeking status both changed, a selected subgroup that may differ in employment, migration, age, disease burden or local policy exposure. Its OR above 1 does not overturn the pooled estimate, just as the repeated-observation subgroup estimate below 1 does not establish a negative insurance effect. The wide intervals show the limited precision of the within-person comparison.

Calendar time is important because the comparison group changed as coverage expanded. By 2015 only 32 eligible uninsured illness observations remained, so insured-versus-uninsured comparisons in later waves had limited overlap and wide uncertainty. The interaction may reflect changes in policy, reimbursement, service capacity, population composition or several of these factors together; the present data cannot isolate a single mechanism. This is why the pooled estimate should not be interpreted as a stable effect across the entire 2004–2015 period.

For health-services evaluation, coverage alone should not be used as a proxy for effective access. High enrollment can coexist with delayed care when reimbursement is limited, services are distant, provider quality is uncertain or uncovered costs remain high. Future analyses should combine insurance status with benefit generosity, actual reimbursement, out-of-pocket expenditure, service availability, travel burden and illness-specific need so that financial protection and realized service use can be evaluated separately.

Strengths include restriction to respondents with a recent illness or injury, repeated-measures GEE, prespecified sensitivity analyses, explicit testing of insurance-by-wave heterogeneity and a within-person comparison. Limitations include self-reported illness, severity, insurance and care seeking; a broad binary insurance measure; grouping different professional providers into one outcome; unavailable data on benefit generosity, household costs and local service supply; possible time-varying confounding; and selection in complete-case and switcher analyses. CHNS is not nationally representative.

The analysis supports a narrower conclusion: the binary insurance indicator available across these CHNS waves was insufficient to characterize professional care seeking after illness. Research designed to estimate policy effects will need scheme-specific benefits, patient cost sharing, local service supply and clearly timed policy or eligibility variation. Those data would allow stronger separation of insurance effects from changing population composition and health-system context.

5 Conclusions

Across 2004–2015, medical-insurance coverage showed no stable pooled association with professional care seeking after recent illness, but the association varied significantly by survey wave. A stronger positive association in 2011 was not reproduced consistently and occurred within a rapidly changing policy environment; by 2015, very few uninsured illness observations remained. Insurance enrollment should not be interpreted as a time-invariant exposure or a sufficient measure of effective access. Future analyses should distinguish insurance schemes and benefit generosity and exploit policy variation with designs better suited to causal inference.

Declarations

Ethics approval and consent to participate

The underlying China Health and Nutrition Survey protocols were reviewed by institutional review boards at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Food Safety/Chinese Center for Disease Control and Prevention, and participants provided written informed consent. This secondary analysis used de-identified data released for research use and involved no new participant recruitment or intervention.

Consent for publication

The manuscript contains no identifiable individual-level information; separate consent for publication was not required.

Competing interests

The authors declare no competing interests.

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Author Contribution

YZ conceived the study, managed the data, conducted the statistical analyses, and drafted the manuscript. JW supervised the study, reviewed the methodology, and critically revised the manuscript. Both authors interpreted the results and read and approved the final manuscript.

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Availability of data and materials

The individual-level CHNS data used in this analysis are available through the UNC Dataverse subject to the repository data-use conditions (doi:10.15139/S3/9PQ5KV). The reproducibility scripts used to generate the analytical results are retained with the study files.

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Figures

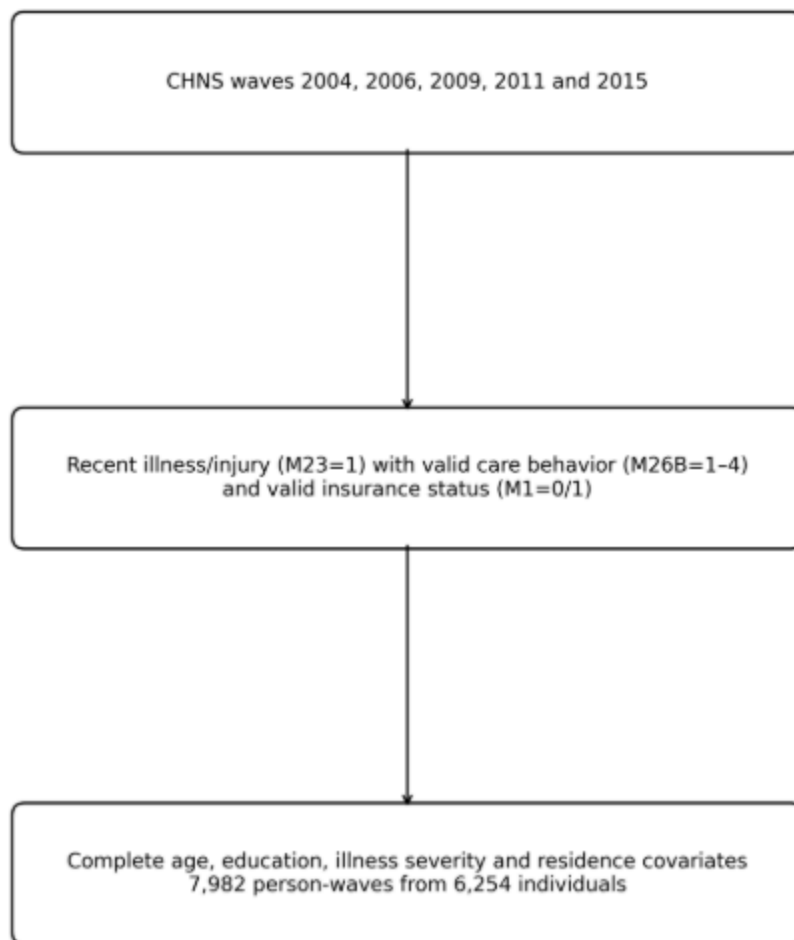


Figure 1

Construction of eligible recent-illness person-wave observations. The flow diagram shows construction of eligible recent-illness person-wave observations from the broader CHNS sample.

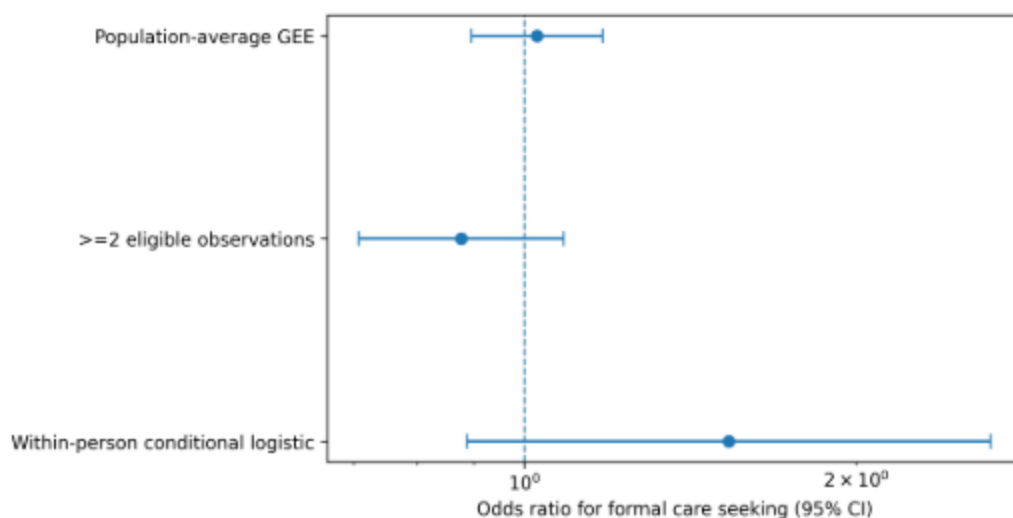


Figure 2

Insurance coverage and professional care seeking across primary and sensitivity analyses. Adjusted odds ratios and 95% confidence intervals are shown for the primary and prespecified sensitivity analyses.

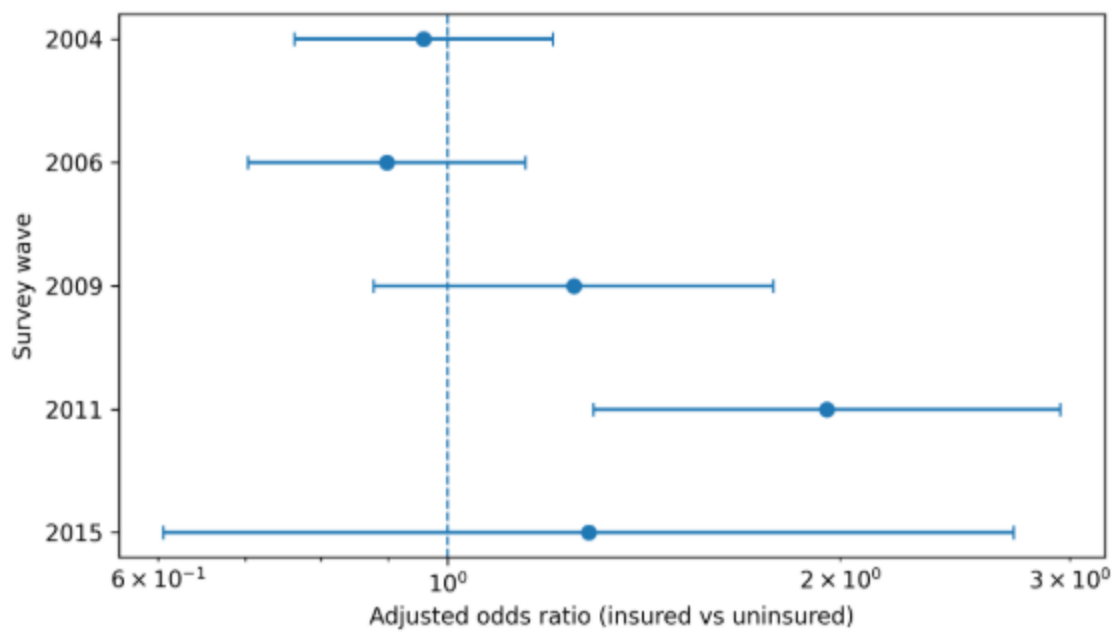


Figure 3

Wave-specific adjusted odds ratios for professional care seeking by insurance status. Wave-specific adjusted odds ratios and 95% confidence intervals are shown; the vertical null line corresponds to OR=1.