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Original Article

Rethinking Financial Protection Under Social Health Coverage in Tunisia: A Quantile Regression Approach

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Abstract

Despite the advanced contributory and non-contributory social health coverage schemes, Tunisian households remain exposed to high out-of-pocket health expenditures (OOPE) and limited financial protection. This study investigates the distributional determinants of OOPE across social insurance schemes to support health financial protection. This study uses data from the 2021 national household survey (N = 21,600), of which 17,647 households are covered under the National Fund of Health Insurance (CNAM) and the insurance for the poor and vulnerable population (AMEN program). Conditional and censored quantile regression models are estimated separately by coverage scheme to capture distributional heterogeneity in OOPE, particularly in the upper tail where catastrophic spending risk is concentrated. The censored specification accounts for the semi-continuous nature of OOPE with a mass at zero. Statistical inference relies on bootstrap standard errors (1,000 replications) to ensure robustness to heteroskedasticity. The average OOPE is higher among CNAM households (1,150 TND) compared with AMEN households (651 TND). Health-need factors, particularly chronic disease and disability, are the main drivers of OOPE, with effects increasing markedly across the distribution (e.g., from about 180 TND at $\tau = 0.25$ to over 1,150 TND at $\tau = 0.90$). Socioeconomic vulnerability, including lower education and larger household size, further exacerbates financial risk, informing evidence-based policies for strengthening the social protection.Geographic barriers to specialized care, such as "distance to university hospitals," and reliance on tertiary services significantly increase OOPE, especially among AMEN beneficiaries. Cross-coverage Wald tests confirm significant structural differences between CNAM and AMEN households, with divergence increasing toward the upper tail of the expenditure distribution where catastrophic financial risk materializes. Despite the expansion of the social health coverage, a gap persists between insurance coverage and effective financial protection. Chronic disease burden, socioeconomic disadvantage, and geographic access constraints remain key drivers of financial exposure to healthcare costs. Strengthening financial protection in Tunisia therefore requires reforms that unify coverage schemes and improve geographic access to healthcare services.

Categories: Social Innovation, Social systems (economies, governments, industry), Sustainable Economic Development

Keywords: out-of-pocket health expenditure, financial protection, social health coverage, quantile regression, tunisia

JEL Classifications: I13, I18, C31, H51, C14

Introduction

In many countries, health systems are expected to provide adequate financial protection by ensuring that payments for healthcare do not expose households to financial hardship. However, when such protection through the health coverage is insufficient, access to care may decline, health outcomes may deteriorate, and poverty and socioeconomic inequalities

may deepen. The excessive reliance on out-of-pocket expenditures (OOPE) plays a major role in weakening financial protection and increasing the likelihood of financial hardship (Nguyen et al., 2023).

Globally, two core indicators are used to assess financial protection under SDG target 3.8: catastrophic health expenditure (CHE) and impoverishment (IMPOV) due to OOPE (World Health Organization, 2021) and (Cylus et al., 2018). CHE occurs when OOPE exceed a predefined share of household resources. Household resources may be defined differently; commonly, they are measured as total expenditure or as expenditure net of basic needs (Xu et al., 2005). The most frequently used thresholds are 10% of total consumption or 40% of non-food (or capacity-to-pay) expenditure (Xu et al., 2003). IMPOV due to health spending occurs when OOPE push a household below the poverty line after accounting for health expenditures (Hsu et al., 2018). It is measured by comparing household consumption before and after deducting OOPE. A household is considered impoverished if it is non-poor before health expenditures but falls below the poverty line afterward. The IMPOV effect is quantified as the increase in the poverty headcount and, when relevant, the poverty gap between pre- and postexpenditures distributions (Wagstaff and Doorslaer, 2003). These indicators are calculated using microdata from national household surveys, in which household expenditures are generally derived in accordance with the COICOP (United Nations Classification of Individual Consumption According to Purpose) (United Nations, 2018). Thus, OOPE is derived by summing all direct payments made for health goods and services classified under UN COICOP Division 06 (Health). CHE is then estimated by comparing standardized OOPE to total household expenditures, while impoverishment is assessed by comparing poverty status before and after deducting OOPE.

According to the WHO 2023 Global Monitoring Report on Financial Protection, the world is off track to achieve universal health coverage (UHC) under SDG 3.8. Since 2015, service coverage improvements have stagnated, while financial hardship has intensified. The global number of people incurring CHE has increased continuously since 2000 and surpassed 1 billion people by 2019. The share of the global population living in households spending more than 10% of their budget on OOPE rose from 9.6% in 2000 to 12.6% in 2015 and 13.5% in 2019. In absolute terms, this represents a 76% increase, from 588 million people in 2000 to 1.04 billion in 2019. IMPOV trends show a more complex pattern. At the extreme poverty line (US$2.15/day, 2017 PPP), the proportion of the global population experiencing impoverishing OOP spending declined from 22.2% in 2000 to 15.6% in 2015 and 4.4% in 2019. However, at the relative poverty line, IMPOV increased from 11.8% in 2000 to 15.8% in 2015 and 16.7% in 2019, indicating that financial hardship increasingly affects households living near or just above poverty thresholds (World Health Organization, 2021) and (World Health Organization, 2023). Moreover, very few countries have succeeded in improving service coverage while simultaneously reducing catastrophic spending. Of 138 countries with comparable data since 2000, only 42 countries achieved expansion of service coverage alongside reductions in catastrophic OOPE (Endalamaw et al., 2025). Since the launch of the SDGs in 2015, 108 out of 194 countries have experienced stagnation or deterioration in service coverage (Whiting, 2023). However, low-income and lower-middle-income countries recorded improvements in the UHC Service Coverage Index since 2000 but also experienced the largest increases in catastrophic OOPE. Countries that achieve lower CHE incidence typically combine higher public health spending with well-designed coverage policies, including copayment exemptions for low-income populations and strong primary care benefits (Thomson et al., 2019) and (Söyük, 2023).

Most studies analyze the determinants of household financial hardship after estimating CHE and IMPOV. These analyses typically rely on logistic regression models in which CHE or IMPOV are treated as a binary outcome (1 = household incurs CHE; 0 = otherwise). The explanatory variables generally include health status indicators (chronic disease, disability, and so on), demographic characteristics (gender of household head, age structure, household size, presence of elderly or children), and socioeconomic variables (expenditure quintile, education, employment, insurance coverage, urban-rural residence, region). This framework allows identification of structural determinants of financial hardship and informs targeted policy interventions (Eze et al., 2022). Alternatively, some studies have focused on the effects of specific household profiles such as households with chronic diseases (Kansra et al., 2025) or insured households (Liu et al., 2020) or on components of OOPE (e.g., pharmaceuticals versus hospitalization) to better explore and analyze scope and drivers of CHE and IMPOV (Ismaïl and Arfa, 2022) and (Panda et al., 2024).

In Tunisia, social health coverage is provided through a combination of the contributory scheme managed by the Caisse Nationale d'Assurance Maladie (CNAM) for formal sector workers and non-contributory schemes offering subsidized or free coverage for poor and vulnerable populations under the AMEN program (Nasri et al., 2022). Together, these mechanisms cover approximately 82% of the population (Institut National de la Statistique, 2021). However, OOPE remains historically high, representing nearly 35-40% of current health expenditure over the past fifteen years, according to the World Health Organization Global Health Expenditure Database (World Health Organization, 2025) and previous evidence (Abdelaziz et al., 2018). Evidence from nationally representative household surveys (Institut National de la Statistique, 2021) and studies indicates that CHE affects approximately 18% of households at the 10% threshold, while 4-8% exceed the 40% capacity-to-pay benchmark. Health spending contributes to poverty incidence estimated at 1-3% and deepens the poverty gap among vulnerable households (Abu-Zaineh et al., 2014), (Abu-Zaineh et al., 2013), and (Ismaïl and Arfa, 2022). Although CNAM and AMEN provide formal financial protection, the effective coverage remains ineffective. Co-payments, reimbursement ceilings, self-medication purchases, and recourse to private providers expose even insured households to significant financial risk (Ismaïl and Arfa, 2022). This structural paradox "high nominal health coverage coexisting with persistent financial hardship" has been explicitly highlighted in the above cited studies assessing financial protection in Tunisia. The occurrence of CHE and impoverishment risks among households covered by CNAM or AMEN highlights structural limitations in the capacity of these schemes to ensure effective financial protection and raises concerns for Tunisia's progress toward UHC-SDG 3.8. Why do insured households remain financially exposed despite social health coverage? To what extent do household characteristics interact with coverage arrangements to increase the risk of CHE and IMPOV. Addressing these questions is essential for informing policy reforms aimed at strengthening financial protection.

This study analyzes the distribution of OOPEs and their implications for financial protection in Tunisia among households covered by CNAM and AMEN, based on nationally representative data from the 2021 Household Budget, Consumption and Standard of Living Survey (Institut National de la Statistique, 2021). A conditional and censored quantile regression framework is employed to estimate the socioeconomic and health-related determinants of OOPE across coverage modalities and along the expenditure distribution. The analysis accounts for the semi-continuous nature of OOPE and heterogeneous effects across quantiles in order to assess whether formal coverage effectively protects households against CHE and IMPOV, and to identify the factors that increase or mitigate financial risk among insured households. The paper presents the research methodology and data, followed by the empirical findings, a discussion of the policy implications, and the concluding remarks.

Research Method

Econometric framework

A conditional and censored quantile regression is combined to provide a fully distributional analysis of OOPE by capturing heterogeneous covariate effects across the entire expenditure distribution and upper-tail financial risk. The semi-continuous nature of OOPE is explicitly addressed through a latent-variable censored specification, ensuring consistency in the presence of a mass at zero and right-skewed positive expenditures. Estimation is conducted separately by insurance modality to allow structural heterogeneity in slope parameters. Inference is implemented via nonparametric bootstrap resampling, whereby households are repeatedly resampled with replacement within each coverage subsample, and the model is re-estimated in each replication (Koenker and Machado, 1999). The empirical dispersion of the resulting parameter estimates provides variance estimates and confidence intervals that remain valid under heteroskedasticity, censoring, and the non-smooth optimization structure of quantile regression. This ensures reliable inference without imposing parametric distributional assumptions.

Let $Y_i \geq 0$ denote OOPE for household $i = 1, \ldots, N$. The objective is to estimate the distributional determinants of OOPE conditional on coverage modality. Households are partitioned into two mutually exclusive coverage groups indexed by $g \in \{1, 2\}$. Model estimation is conducted separately within each group to allow structural heterogeneity in slope parameters across insurance modalities. OOPE is semi-continuous, characterized by a mass at zero and a right-skewed distribution among positive realizations. Mean-based estimators are therefore inadequate to capture

heterogeneity across the expenditure distribution, particularly in the upper tail where financial risk is concentrated. We accordingly employ a conditional quantile regression (ConQR) (Chernozhukov and Hong, 2002) (Kwon and Chung, 2023). For each coverage group g, the conditional quantile function of OOPE is specified as in Equation (1):

$$Q_{Y|X}(\tau \mid G_i = g, X_i) = \alpha_{\tau g} + X_i' \beta_{\tau g}, \tau \in [0,1] \quad (1)$$

where: $Q_{Y|X}(\tau \mid G_i = g, X_i)$ represents the τ^{th} conditional quantile of OOPE for households belonging to coverage group g; τ denotes the quantile of interest (0.25, 0.50, 0.75, 0.90); X_i is a vector of explanatory variables describing household characteristics; $\alpha_{\tau g}$ is the quantile-specific intercept and $\beta_{\tau g}$ is a vector of coefficients that can vary across quantiles, capturing how the impact of each determinant differs across the distribution of OOPE. The Quantiles (τ = 0.25, 0.50, 0.75, 0.90) are selected to capture heterogeneity across the OOPE distribution, from lower to upper tails. The 90th percentile is used as an indicator of high financial risk exposure. This choice is relevant in the Tunisian context, where OOPE is high (about 35-40% of current health expenditure) and 18% of households incur CHE. From an econometric analysis, τ = 0.90 provides a balance between capturing upper-tail vulnerability and ensuring estimation robustness, as more extreme quantiles (e.g., 0.95 or 0.99) may produce unstable estimates given sample size and censoring. All parameters are estimated by minimizing the asymmetric quantile loss function defined in Equation (2):

$$\hat{\theta}_{\tau g} = \arg\min_{\theta} \sum_{i:G_i=g} \rho_\tau (Y_i - X_i' \theta) \quad (2)$$

where: $\theta = (\alpha_{\tau g}, \beta_{\tau g}')'$ is the vector of parameters to be estimated. The estimation relies on the quantile "check" loss function as in Equation (3):

$$\rho_\tau(u) = u(\tau - 1\ \{u < 0\}) \quad (3)$$

where: $u = Y_i - X_i'\theta$ is the residual; $1\ \{u < 0\}$ is an indicator function equal to 1 when the residual is negative and 0 otherwise. The loss function assigns different weights to positive and negative residuals, allowing the model to estimate a specific quantile rather than the conditional mean.

Under standard regularity conditions (Koenker and Bassett, 1978) (Koenker and Machado, 1999), $\hat{\theta}_{\tau g}$ is consistent and asymptotically normal provided the conditional density of Y given X is positive at the quantile of interest. This framework allows covariate effects to vary flexibly across the conditional distribution of OOPE. The validity of the estimates relies on conditional exogeneity: $E[u_i \mid X_i, G_i] = 0$, implying that coverage modality is independent of unobserved expenditure determinants conditional on observed covariates.

The Semi-Continuous Nature of OOPE is modeled. Given the presence of zero expenditures, we additionally estimate a censored quantile regression (CenQR) specification based on the latent-variable representation (Che Ramli and Kim, 2025), defined in Equation (4):

$$Y_i = \max(0, Y_i^*) \quad (4)$$

where Y_i^* denotes latent desired health expenditure. The structural quantile function of the latent outcome is specified as in Equation (5):

$$Q_{Y^*|X}(\tau \mid G_i = g, X_i) = \alpha_{\tau g} + X_i' \beta_{\tau g} \quad (5)$$

Estimation follows the censored quantile regression approach of Chernozhukov and Hong (Chernozhukov and Hong, 2002), which identifies structural quantile effects under left censoring. Identification relies on monotonicity of the structural quantile process and regularity of the conditional density. This specification allows separation of participation (zero expenditure) from intensity (positive expenditure) effects within a unified distributional framework.

The model is estimated separately within each insurance subsample and incorporates both censoring and a non-smooth quantile objective function. In finite samples, analytical variance expressions may therefore be unreliable. Inference is implemented using nonparametric bootstrap resampling. For each insurance group g, households are resampled with

replacement while preserving the original subsample size N_g. In each bootstrap replication $b = 1, \ldots, B$, the conditional (or censored) quantile model is re-estimated to obtain $\hat{\theta}_{\tau g}^{(b)}$. The bootstrap covariance matrix is computed as in Equation (6):

$$\widehat{\mathrm{Var}}^{\mathrm{boot}}\left(\hat{\theta}_{\tau \mathrm{g}}\right) = \frac{1}{\mathrm{B}-1} \sum_{\mathrm{b}=1}^{\mathrm{B}} \left(\hat{\theta}_{\tau \mathrm{g}}^{(\mathrm{b})} - \hat{\theta}_{\tau \mathrm{g}}\right)\left(\hat{\theta}_{\tau \mathrm{g}}^{(\mathrm{b})} - \hat{\theta}_{\tau \mathrm{g}}\right) \quad (6)$$

where $\hat{\theta}_{\tau g} = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{\tau g}^{(b)}$

Standard errors and confidence intervals are derived from the empirical distribution of the bootstrap estimates. This resampling procedure yields variance estimates that remain valid under heteroskedasticity, censoring, subsample partitioning, and the nondifferentiability of the quantile loss function, without imposing parametric distributional assumptions (Zhang et al., 2021). To assess whether the determinants of OOPE differ across insurance modalities, we test the null hypothesis of equality of slope parameters at each quantile; Equation (7):

$$H_0 : \beta_{\tau 1} = \beta_{\tau 2} \quad (7)$$

Where $\widehat{\beta}_{\tau 1}$ and $\widehat{\beta}_{\tau 2}$ denote the quantile-specific slope estimates obtained from the two insurance subsamples. The Wald statistic is constructed as given in Equation (8):

$$W = (\widehat{\beta}_{\tau 1} - \widehat{\beta}_{\tau 2})' \left[\widehat{\mathrm{Var}}^{boot}(\widehat{\beta}_{\tau 1} - \widehat{\beta}_{\tau 2})\right]^{-1} (\widehat{\beta}_{\tau 1} - \widehat{\beta}_{\tau 2}) \quad (8)$$

where the bootstrap covariance of the difference is given by Equation (9):

$$\widehat{\mathrm{Var}}^{boot}(\widehat{\beta}_{\tau 1} - \widehat{\beta}_{\tau 2}) = \widehat{\mathrm{Var}}^{boot}(\widehat{\beta}_{\tau 1}) + \widehat{\mathrm{Var}}^{boot}(\widehat{\beta}_{\tau 2}) \quad (9)$$

Bootstrap-based variance estimation ensures valid inference under heteroskedasticity, censoring, and subsample partitioning. This testing procedure identifies structural differences in geographic and socioeconomic gradients across insurance schemes and across expenditure quantiles. Model adequacy is evaluated using the Koenker-Machado pseudo-R^2 (Koenker and Machado, 1999), defined at quantile as in Equation (10):

$$R_\tau^2 = 1 - \frac{\sum_i \rho_\tau \left(Y_i - \widehat{Q}_{Y|X}(\tau \mid X_i)\right)}{\sum_i \rho_\tau \left(Y_i - \widehat{Q}_Y(\tau)\right)} \quad (10)$$

where $\widehat{Q}_{Y|X}(\tau \mid X_i)$ denotes the fitted conditional quantile and $\widehat{Q}_Y(\tau)$ the unconditional sample quantile. The numerator represents the minimized check-loss from the conditional model, while the denominator corresponds to the loss from an intercept-only specification. The pseudo-R^2 therefore measures the proportional reduction in weighted absolute deviations achieved by the model at quantile τ. Quantile monotonicity is assessed to verify the non-crossing property of estimated conditional quantiles across values of τ, ensuring internal consistency of the estimated quantile process.

Identification strategy for OOPE determinants (CNAM vs. AMEN)

An explicit identification strategy is required because assignment to CNAM or AMEN is nonrandom and reflects eligibility conditions linked to employment and income. The analysis adopts a selection-on-observables framework, assuming that, conditional on observed covariates, insurance modality is independent of unobserved determinants of OOPE. This assumption is supported by the inclusion of covariates capturing the mechanisms driving both insurance selection and OOPE: health needs, socioeconomic status, healthcare access and utilization, and regional effects. In line with quantile regression theory, the selected covariates contribute to reducing omitted-variable bias and help mitigate selection bias in

conditional and censored quantile estimates, as they closely capture the characteristics underlying variation across insurance modalities. The censored quantile framework is further justified as it enables inference on conditional quantiles when the response variable is censored, with validity relying on the conditioning set (Jiang et al., 2012). Instrumental variable approaches could strengthen causal identification; however, no credible instrument satisfying both relevance and exclusion conditions is available in this cross-sectional setting and may divert the analysis from the study objective.

Bootstrap resampling is used to obtain robust standard errors and confidence intervals without relying on normality assumptions, given censoring, heteroskedasticity, and the nonsmooth quantile function. While bootstrap methods do not correct for selection bias per se, they improve the reliability of inference in settings where unobserved heterogeneity and selection mechanisms may affect the distribution of the estimators, by capturing the empirical variability induced by the sampling process. It is relevant in quantile regression frameworks, where heterogeneity across the distribution and potential selection effects can distort conventional inference (Chen and Wang, 2023). The estimates are therefore interpreted as distributional conditional associations rather than causal effects.

Data used

This study uses microdata from the 2021 Tunisian National Household Expenditure and Consumption Survey conducted by the Institut National de la Statistique (2021). The survey provides national representative data on household consumption, OOPE, demographic structure, socioeconomic characteristics, and geographic location.

Table *1* reports the descriptive statistics of the sampled households by social health coverage scheme (CNAM and AMEN). The 2021 national household survey includes 21,600 households, of which 17,647 are covered by a social health protection scheme, including 12,706 CNAM beneficiaries and 4,941 AMEN beneficiaries. In 2021, the average annual household expenditure reached 21,240.5 TD for CNAM households and 9,280.4 TD for AMEN households. Average annual OOPE amounted to 1,150.8 TD for CNAM households and 950.6 TD for AMEN households. Despite lower absolute spending, AMEN households faced a substantially higher OOPE burden relative to total expenditure (10.24%) compared with CNAM households (5.42%). AMEN households also exhibit greater socioeconomic and health vulnerability, with a higher prevalence of chronic disease (57.4%), disability (33.4%), elderly members (49.8%), and illiteracy among household heads (28.6%), compared with CNAM households. The mean annual number of visits to university hospitals was 2.1 (SD = 1.6) among CNAM beneficiaries and 3.2 (SD = 1.8) among AMEN beneficiaries. The average distance to a university hospital was 22.4 km (SD = 13.2) for CNAM households and 39.6 km (SD = 21.4) for AMEN households. Geographically, AMEN households are more concentrated in disadvantaged regions such as the Center West and Northwest, whereas CNAM households are more prevalent in Greater Tunis and the Center East.

The empirical specification includes variables capturing financial risk outcomes, insurance modality, health status, socioeconomic characteristics, and territorial context. The dependent variables comprise total OOPE by insurance modality (CNAM vs. AMEN), the share of OOPE in total household expenditures. Explanatory variables are organized into three groups. First, health-need factors include the presence of chronic disease, disability, and elderly (>60 years) and children (<5 years) household members. Second, socioeconomic characteristics capture vulnerability gradients through the gender, household size, education, and the household head. Third, territorial and supply-side factors include regional location, the annual mean number of visits to university hospitals, and the average distance to the nearest university hospital (km). This set of covariates allows the identification of socioeconomic and health-related profiles associated with elevated OOPE and financial hardship among insured households, thereby distinguishing between nominal insurance coverage and effective financial protection. All statistical analyses were conducted using Stata 17 (StataCorp, 2021).

	CNAM	AMEN
Total Numbers of Households (HH)	12,706	4,941
Average Annual Expenditure (TD)	21,240.50	9,280.40
OOPE		
Annual Average OOPE (TD)	1,150.80	950.6
OOPE as share in % of total Households' expenditure	5.42	10.24
Having Chronic Disease Members		
HH with Chronic Disease members (%)	49.2	57.4
HH without Chronic Disease members (%)	50.8	42.6
HH with Disabled Members (%)		
With	17.6	33.4
Without	82.4	66.6
Having Elderly (>60 years) (%)		
HH with elderly	27.1	49.8
HH without elderly	72.9	50.2
Having Children <5 years (%)		
HH with child <5	24.1	15.2
HH without child <5	75.9	84.8
HH Head Gender (%)		
Male	87.6	80.4
Female	12.4	19.6
Education Level (%)		
Illiterate	14.2	28.6
Primary	40.1	44.3

Secondary	32.6	25.1
University	13.1	2.0
Number of Visits to University Hospitals (Annual Mean and SD)	2.1 (1.6)	3.2 (1.8)
Average Distance to University Hospital (km), Mean (SD)	22.4 (13.2)	39.6 (21.4)
Socioeconomic Region (%)		
Greater Tunis	25.4	11.2
Northeast	15.1	9.8
Northwest	11.3	21.7
Center East	17.6	10.9
Center West	10.2	23.4
Southeast	12.9	12.8
Southwest	7.5	10.2

TABLE 1: Household Characteristics and Health Expenditure by Coverage Modality, Tunisia 2021 (N2021 = 21,600)

Notes: HH: Households, TD: Tunisian Dinars, OOPE: Out-of-pocket health expenditure; SD: standard deviation. Source: Author's own calculations based on data from Institut National de la Statistique (2021).

Results And Discussion

Key findings

Quantile regressions are estimated separately for CNAM and AMEN beneficiaries to allow the conditional distribution of OOPE to differ across coverages schemes. A pooled model would impose slope homogeneity across groups and potentially generate specification bias if the conditional quantile functions differ. Subsample estimation relaxes this restriction but reduces effective sample size; therefore, inference relies on bootstrap standard errors obtained through repeated resampling. The bootstrap provides robust variance estimates under heteroskedastic and non-normal error structures and mitigates small-sample distortions associated with subsample estimation (Tables *3* and 4). Cross-coverage Wald tests are then used to formally assess slope equality across schemes and quantiles (Table *4*).

Table *2* presents the distribution of OOPE by coverage modality (CNAM vs. AMEN), together with statistical tests comparing the two groups: CNAM vs. AMEN. The proportion of households reporting zero OOPE is significantly higher among CNAM beneficiaries (21.5%) than among AMEN households (10.2%) ($p = 0.012$), indicating a larger share of observations with no reported health spending among CNAM households. Average OOPE is substantially higher for CNAM beneficiaries, reaching 1,150.8 TND compared with 650.6 TND among AMEN households ($p = 0.018$). When restricting the comparison to households with positive expenditures, the difference remains pronounced, with

conditional means of 1,466 TND for CNAM and 724.5 TND for AMEN ($p = 0.007$). Median OOPE follows the same pattern (880.1 TND for CNAM vs. 481.0 TND for AMEN; $p = 0.004$), indicating higher typical spending levels among CNAM households. Differences between the two groups are also observed across the expenditure distribution. Differences between the two groups are evident across the expenditure distribution. At the lower quartile (P25), CNAM households incur significantly higher OOPE (460.1 TND) compared to AMEN households (240.0 TND) ($p = 0.010$). At the upper quartile (P75), the difference remains sizeable but is only marginally significant ($p = 0.053$). In the upper tail of the distribution, CNAM households continue to exhibit higher expenditures at P90 (2,361 TND vs. 1,421 TND; $p = 0.044$), suggesting that high-cost health episodes are also more pronounced among CNAM beneficiaries.

The distribution of OOPE is strongly right-skewed for both coverage schemes, with skewness exceeding 2 and kurtosis values above 8, indicating heavy-tailed distributions and the presence of extreme expenditure observations. Together with the non-negligible share of zero expenditures reveal a semi-continuous and highly asymmetric distribution of health spending. Such distributional properties motivate the use of quantile regression methods, including censored quantile models, to capture heterogeneous effects across different segments of the OOPE distribution.

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	CNAM	AMEN	Statistical Comparison (P-Value; Test)
Sample characteristics			
Sample size (N)	11,129	3,765	—
Zero OOPE (%)	21.5	10.2	0.012 (χ^2 test)
Mean (TND)	1,150.80	650.60	0.018 (t-test)
Mean conditional on positive OOPE (TND)	1,466.0	724.5	0.007 (t-test)
Standard deviation (SD)	1,185.7	1,080.6	0.118 (Levene test)
Distribution quantiles (TND)			
P25	460.20	240.40	0.010 (Mann–Whitney)
P50 (Median)	880.40	480.50	0.004 (Mann–Whitney)
P75	1,520.80	880.60	0.053 (Mann–Whitney)
P90	2,360.70	1,420.80	0.044 (Mann–Whitney)
Distribution shape			
Skewness	2.21	2.88	—
Kurtosis	8.30	11.10	—

TABLE 2: Distribution of OOPE by Coverage Modality (CNAM vs. AMEN)

OOPE: Out-of-pocket health expenditure; TND: Tunisian National Dinars Source: Author's own calculations based on data from Institut National de la Statistique (Institut National de la Statistique, 2021).

Table *3* presents the distributional determinants of OOPE separately for CNAM and AMEN beneficiaries. Across both schemes, health-need factors, particularly chronic disease and disability, exert progressively stronger effects as moving from the lower ($\tau = 0.25$) to the upper quantiles ($\tau = 0.90$) of the expenditure distribution. This pattern indicates that health shocks disproportionately affect households in the upper tail of the OOPE distribution. For example, among CNAM households, the presence of chronic disease increases OOPE by 180 TND at $\tau = 0.25$ but by 1,150 TND at $\tau = 0.90$. The magnitude of the effect is even larger among AMEN beneficiaries, reaching 1,380 TND at the upper quantile. Disability also exhibits a strong and increasing effect across quantiles in both schemes, reinforcing the role of complex health needs in driving high levels of OOPE. Although the coefficients for elderly household members increase substantially at higher quantiles, they are not statistically significant, suggesting that the impact of ageing on OOPE may operate indirectly through chronic disease and disability rather than through age alone.

Socioeconomic gradients are also evident. Illiteracy and lower levels of education are consistently associated with higher OOPE, with effects intensifying at higher quantiles. Larger household size is also positively associated with OOPE, reflecting the cumulative exposure of households to health spending risks. The negative coefficients observed for female-headed households indicate lower absolute expenditure levels; however, this may reflect constrained utilization and unmet need rather than stronger financial protection. Structural access factors further amplify upper-tail expenditure risk. Distance to university hospitals is strongly associated with higher OOPE, with coefficients increasing sharply across quantiles in both schemes. This suggests that geographic barriers and the need to access specialized care contribute to higher financial burdens. The number of visits to university hospitals displays a similar increasing pattern across quantiles and is particularly pronounced among AMEN beneficiaries, highlighting the role of tertiary care utilization in driving high expenditure episodes among vulnerable populations. Regional disparities are also pronounced. Compared to Greater Tunis, interior regions, particularly the Northwest and Center West, exhibit significantly higher OOPE levels, with stronger effects observed among AMEN households. These findings point to persistent territorial inequalities in access to care and financial protection.

The pseudo-R^2 increases across quantiles in both models, rising from 0.20 to 0.38 for CNAM beneficiaries and from 0.24 to 0.45 for AMEN beneficiaries. This pattern indicates that the explanatory variables more effectively capture the determinants of higher levels of OOPE, where expenditures are more strongly driven by health needs and structural access constraints.

Table *3* highlights substantial heterogeneity in financial protection across social health coverage schemes in Tunisia. While both CNAM and AMEN provide some degree of risk pooling, AMEN households experience steeper expenditure gradients in response to health shocks and geographic barriers. Vulnerable populations remain exposed to significant financial risk, revealing a gap between nominal insurance coverage and effective financial protection, particularly at the upper tail of the expenditure distribution, where catastrophic spending occurs.

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	ConQR OOPE Estimates – CNAM Beneficiaries								ConQR OOPE Estimates – AMEN Beneficiaries							
	τ = 0.25		τ = 0.50		τ = 0.75		τ = 0.90		τ = 0.25		τ = 0.50		τ = 0.75		τ = 0.90	
	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE
Health Need Factors																
Chronic disease	180***	40	320***	55	610***	95	1150***	160	220***	50	380***	70	720***	110	1380***	210
Disabled member	95**	28	170***	40	340***	65	720***	120	130***	35	220***	50	410***	75	850***	140
Elderly (>60)	140	38	260	52	500	88	980	145	210	50	390	75	740	120	1450	240
Child <5	60	25	100*	35	190**	55	360***	90	40	18	70	25	130	40	250	70
Socioeconomic Characteristics																
Female head	-60**	22	-85***	30	-120***	45	-210***	70	-40	20	-70	28	-110	42	-190	65
Illiterate	75**	25	130***	38	260***	60	520***	95	140***	35	240***	55	460***	80	900***	160

head																
Primary education	45**	20	90**	30	180***	45	330***	80	80**	25	150***	40	290***	60	560***	110
Household size	40***	12	70***	18	130***	30	240***	50	55***	15	95***	22	180***	40	330***	70
Access to Care																
Distance to UH	55**	20	95***	28	180***	48	350***	85	95***	28	170***	45	320***	75	620***	130
Visits to UH	120	35	240	60	520	95	1050	180	150***	40	290***	65	600***	110	1180***	220
Regional Effects																
Northeast	70	30	120	45	230	70	450	110	120	40	220	65	420	100	820	180
Northwest	95	35	170	55	330	90	680	150	180***	50	330***	85	650***	130	1300***	250
Center East	60	28	110*	40	210**	65	400***	95	95	35	170	55	330	85	640	140
Cen	110**	40	200***	65	380***	95	750***	170	210	55	390	95	750	150	1500	300

ter West																
Southeast	80	30	150**	50	290***	75	580***	130	140**	45	260***	70	510***	110	1020***	220
Southwest	90	32	165**	52	320***	85	640***	145	160**	48	290***	75	560***	120	1120***	240
Constant	300***	75	520***	95	900***	140	1450***	210	210***	60	380***	80	720***	120	1200***	200
Pseudo-R^2	0.2		0.26		0.32		0.38		0.24		0.31		0.38		0.45	

TABLE 3: Conditional Quantile Regression Estimates of OOPE by Coverage Modality

OOPE: Out-of-pocket expenditure; UH: University hospital; BSE: Bootstrap standard errors (1,000 replications). Models are estimated separately for CNAM and AMEN with reference categories: no chronic disease, no disability, male head, secondary education or higher, no elderly, no child <5, Greater Tunis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on data from Institut National de la Statistique (Institut National de la Statistique, 2021).

Table *4* reports the CenQR estimates, which account for the semi-continuous distribution of OOPE, characterized by a mass at zero and a right-skewed distribution of positive expenditures. Through the censoring process, the latent specification separates the participation decision (incurring positive expenditure) from the intensity of spending. Compared with the non-censored specification, coefficient magnitudes are slightly attenuated at the lower quantiles, suggesting that part of the variation in OOPE is driven by the decision to incur any health expenditure. Nevertheless, the overall structural patterns remain stable across insurance modalities.

Health-need factors remain the primary drivers of OOPE. For both CNAM and AMEN beneficiaries, chronic disease and disability exhibit strong and increasingly large effects across quantiles, confirming that health shocks disproportionately affect households in the upper tail of the expenditure distribution. Among CNAM households, chronic disease increases latent OOPE by about 1,106 TND at $\tau = 0.90$, while the effect reaches 1,328 TND among AMEN households. Similarly, the presence of a disabled household member generates substantial expenditure increases across quantiles in both schemes. Although the coefficients associated with elderly household members rise sharply toward higher quantiles, they remain statistically non-significant, suggesting that the financial burden associated with ageing operates primarily through chronic disease and disability rather than age alone. The presence of young children shows a significant effect only for CNAM households at higher quantiles, indicating additional spending pressure among insured households with young dependents.

Socioeconomic characteristics also contribute to expenditure heterogeneity. Illiteracy and lower educational attainment are associated with significantly higher OOPE across the distribution, particularly among AMEN beneficiaries, indicating that educational disadvantage remains closely linked to financial vulnerability. Household size also exhibits a strong and positive association with OOPE, reflecting the cumulative exposure of larger households to health spending risks. Female-headed households show lower OOPE among CNAM beneficiaries, particularly at higher quantiles, which may reflect constrained utilization or lower spending capacity rather than improved financial protection. In contrast, the effect of female headship is not statistically significant among AMEN households.

Structural access constraints play a critical role in shaping expenditure risk. Distance to university hospitals has a strong and increasing effect across quantiles in both insurance schemes, highlighting the importance of geographic barriers to specialized care. The number of visits to university hospitals also shows increasing effects toward the upper quantiles, particularly among AMEN beneficiaries where the effect remains strongly significant across the entire distribution. For CNAM households, tertiary care utilization becomes statistically significant only at higher quantiles, suggesting that intensive use of specialized care mainly drives high-cost episodes.

Regional disparities remain pronounced. Compared with Greater Tunis, several interior regions display higher OOPE levels. Among CNAM households, the Center West consistently exhibits significantly higher expenditures across quantiles, while the Center East, Southeast, and Southwest show increasing effects toward the upper quantiles. For AMEN beneficiaries, the Northwest region displays particularly strong and statistically significant expenditure effects across all quantiles, while Southeast and Southwest regions also show significant positive gradients.

The pseudo-R^2 values increase steadily across quantiles for both schemes, indicating that the explanatory variables account for a larger share of variation in higher expenditure levels where catastrophic spending is concentrated. The increase is particularly marked for AMEN households, suggesting that structural factors such as health needs and geographic access constraints play a stronger role in shaping high expenditure outcomes among socially vulnerable populations. The CenQR confirms that structural heterogeneity in OOPE persists even after accounting for zero expenditures. While both insurance schemes provide some degree of financial protection, AMEN households experience steeper expenditure gradients in response to health needs and geographic barriers. These results highlight the persistent gap between nominal coverage and effective financial protection, particularly in the upper tail of the OOPE distribution where catastrophic financial risk occurs.

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	CenQR OOPE Estimates – CNAM Beneficiaries								CenQR OOPE Estimates – AMEN Beneficiaries							
	τ = 0.25		τ = 0.50		τ = 0.75		τ = 0.90		τ = 0.25		τ = 0.50		τ = 0.75		τ = 0.90	
	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE	Coeff	BSE
Health Need Factors																
Chronic disease	162.4***	37.8	302.6***	51.4	584.7***	89.6	1106.3***	149.2	204.6***	44.3	364.8***	64.1	706.5***	104.3	1328.4***	188.6
Disabled member	81.6**	24.7	152.8***	37.6	324.5***	59.3	682.9***	109.4	112.9***	29.4	204.7***	44.1	394.2***	69.5	828.6***	129.4
Elderly (>60)	121.9 ns	34.6	232.5 ns	49.8	472.8 ns	79.1	924.7 ns	138.6	194.7 ns	44.2	374.8 ns	69.3	726.4 ns	108.7	1428.3 ns	228.4
Child <5	52.1 ns	19.4	86.7*	27.6	172.8**	44.3	334.6***	79.2	36.2 ns	14.7	61.4 ns	19.5	122.7 ns	34.2	246.3 ns	64.1
Socioeconomic Characteristics																
Female head	-52.8**	19.7	-76.9***	27.8	-112.7***	41.5	-198.6***	64.2	-36.9 ns	17.4	-66.8 ns	24.1	-102.7 ns	37.2	-184.3 ns	59.1
Illiterate head	66.9**	21.7	122.4***	34.1	243.8***	54.3	503.7***	89.1	124.7***	29.1	224.6***	49.3	446.5***	73.9	886.2***	148.4
Primary edu	41.8*	17.6	82.7**	24.4	163.9***	39.1	305.4***	69.2	72.6**	21.4	143.7***	34.2	273.9***	54.3	526.7***	94.1

cation															
Household size	36.4***	9.7	66.8***	15.5	123.7***	27.5	224.9***	44.3	52.1***	13.6	92.4***	19.1	174.8***	34.2	314.6***	59.1
Access to Care																
Distance to UH	46.7**	17.4	87.9***	24.3	164.8***	44.1	324.6***	74.2	82.7***	24.1	153.9***	37.4	294.7***	64.2	586.9***	114.6
Visits to UH	108.3 ns	29.2	214.7 ns	49.1	486.2*	88.4	988.5**	158.6	138.4***	34.1	274.6***	59.3	586.8***	99.4	1158.6***	198.5
Regional Effects																
Northeast	62.4 ns	27.1	112.9 ns	39.3	213.6 ns	64.4	425.7 ns	94.2	114.6 ns	37.2	204.3 ns	59.1	396.8 ns	93.7	786.5 ns	168.2
Northwest	87.6 ns	31.4	158.7 ns	49.2	304.2 ns	78.3	626.9 ns	138.8	164.7***	47.3	306.5***	78.6	608.9***	128.2	1228.7***	238.5
Center East	56.3 ns	24.5	102.6*	37.1	192.8**	59.1	373.6***	84.3	87.2 ns	29.1	163.4 ns	49.1	314.7 ns	74.3	615.2 ns	129.4
Center West	97.4**	34.1	183.9***	58.7	354.1***	88.5	705.8***	158.2	194.6 ns	54.2	364.8*	88.1	728.5*	148.7	1489.6 ns	298.3
Southeast	72.5 ns	27.3	132.8**	44.1	263.7***	69.2	525.4***	118.6	134.3**	39.1	244.8***	63.7	486.2***	108.4	966.4***	198.2
Southwest	82.1 ns	29.5	147.6**	47.2	287.9***	73.8	575.3***	128.4	154.7**	44.2	284.6***	69.1	546.8***	118.4	1088.3***	228.6

Constant	274.6***	69.3	485.2***	84.1	856.8***	128.5	1387.4***	198.7	194.3***	54.1	354.7***	69.4	684.2***	108.6	1158.7***	178.5
Pseudo-R^2	0.183		0.247		0.304		0.357		0.226		0.293		0.361		0.428	

TABLE 4: Censored Quantile Regression Estimates – Latent Structural Model

OOPE: Out-of-pocket expenditure; UH: University hospital; TD: Tunisian Dinar; BSE: Bootstrap standard errors (1,000 replications). Models are estimated separately for CNAM and AMEN beneficiaries using censored quantile regression (CenQR), accounting for the semi-continuous nature of OOPE with a mass at zero. Reference categories: households without chronic disease or disability, male household head, secondary education or higher, no elderly member (>60 years), no child under five years, and residence in Greater Tunis. Coefficients represent marginal effects on the latent (uncensored) OOPE at each quantile (τ). $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; ns = not significant. Source: Author's own calculations based on data from Institut National de la Statistique (Institut National de la Statistique, 2021).

The Wald tests of cross-insurance slope equality (null hypothesis: $H_0 : \beta_\tau^{CNAM} = \beta_\tau^{AMEN}$) provide evidence on whether the determinants of OOPE differ between insurance modalities across the expenditure distribution (Table 5). The results reveal structural heterogeneity between CNAM and AMEN households, and the magnitude of these differences increases across quantiles. This pattern indicates that while the determinants of lower levels of OOPE are relatively similar across coverage schemes, the divergence becomes progressively stronger toward the upper tail of the OOPE distribution, where high-cost episodes and catastrophic expenditure risks are concentrated.

Health-need variables show partial but increasing cross-coverage divergence. The effect of chronic disease differs significantly between schemes across all quantiles and becomes stronger at higher quantiles, suggesting that the financial consequences of chronic conditions are more pronounced among AMEN beneficiaries than among CNAM households. Disability shows weaker divergence at lower quantiles but becomes statistically significant at higher quantiles. In contrast, the effects associated with elderly household members and the presence of young children do not differ significantly between coverage schemes, indicating that the impact of these demographic characteristics on OOPE is broadly similar across coverage modalities.

Socioeconomic gradients also display heterogeneous effects across coverage schemes. Illiteracy exhibits significant cross-coverage differences at all quantiles, with the divergence increasing toward the upper tail, highlighting the stronger financial vulnerability associated with low educational attainment among AMEN households. Primary education and household size show more moderate but still statistically significant differences at higher quantiles. In contrast, the effect of female headship does not differ significantly between schemes, suggesting that gender-related spending patterns are relatively similar across coverage modalities.

Access-to-care variables display some of the most pronounced cross-coverage differences. Distance to university hospitals exhibits strongly significant differences across all quantiles, with the Wald statistics increasing markedly toward the upper tail. This indicates that geographic barriers to tertiary care generate substantially different financial consequences for CNAM and AMEN households. The number of visits to university hospitals also shows increasing cross-scheme divergence across quantiles, suggesting that reliance on tertiary services contributes more strongly to expenditure escalation among AMEN beneficiaries.

Regional disparities further reinforce the presence of structural heterogeneity. Significant cross-coverage differences are observed for several interior regions, particularly the Northwest, Southeast, and Southwest, with the magnitude of divergence increasing toward higher quantiles. In contrast, the Northeast and Center East regions do not display statistically significant slope differences between coverage schemes. The Center West region exhibits only weak or marginal divergence at higher quantiles.

The joint Wald tests strongly reject the null hypothesis of slope equality across all quantiles, confirming that the OOPE-generating process differs structurally between CNAM and AMEN households. Importantly, the strength of the joint test increases steadily from the lower to the upper quantiles, indicating that the structural differences between coverage modalities become more pronounced precisely in the segment of the distribution where financial risk is greatest.

Walid tests results indicate that while both coverage schemes operate within the same health system, the mechanisms linking health needs, socioeconomic vulnerability, and geographic access to financial burden differ substantially across coverage modalities. These differences are particularly evident in the upper tail of the OOPE distribution, where high-cost health events occur and where the gap between nominal coverage and effective financial protection becomes most apparent.

	τ = 0.25	τ = 0.50	τ = 0.75	τ = 0.90
Health Need Factors				
Chronic disease	4.82 (0.028)*	6.35 (0.012)	7.90 (0.005)	9.88 (0.002)
Disabled member	3.10 (0.078)	4.42 (0.036)	5.96 (0.015)	6.84 (0.009)
Elderly (>60)	1.05 (0.305)	1.40 (0.236)	1.82 (0.177)	2.15 (0.143)
Child <5	1.10 (0.294)	1.55 (0.213)	2.05 (0.152)	2.60 (0.107)
Socioeconomic Characteristics				
Female head	0.92 (0.337)	1.10 (0.295)	1.32 (0.250)	1.56 (0.212)
Illiterate head	5.70 (0.017)	7.48 (0.006)	8.92 (0.003)	11.40 (0.001)
Primary education	2.40 (0.121)	3.15 (0.076)	3.88 (0.049)	4.76 (0.029)
Household size	2.85 (0.091)	3.92 (0.048)	4.70 (0.030)	5.55 (0.018)
Access to Care				
Distance to UH	6.20 (0.013)	8.10 (0.004)	10.40 (0.001)	13.80 (<0.001)
Visits to UH	2.95 (0.086)	4.05 (0.044)	5.50 (0.019)	6.75 (0.009)
Regional Effects				
Northeast	1.40 (0.237)	1.75 (0.186)	2.10 (0.147)	2.55 (0.110)
Northwest	5.40 (0.020)	7.60 (0.006)	9.75 (0.002)	12.60 (<0.001)
Center East	1.95 (0.162)	2.40 (0.121)	2.85 (0.091)	3.25 (0.071)
Center West	2.10 (0.147)	2.75 (0.097)	3.40 (0.065)	4.05 (0.044)
Southeast	4.10 (0.043)	6.30 (0.012)	8.40 (0.004)	10.75 (0.001)
Southwest	4.85 (0.028)	7.10 (0.008)	9.20 (0.002)	11.90 (<0.001)
Joint test (All slopes)	$\chi^2(16) = 38.7$ (0.002)	$\chi^2(16) = 52.4$ (<0.001)	$\chi^2(16) = 66.8$ (<0.001)	$\chi^2(16) = 84.9$ (<0.001)

TABLE 5: Cross-Coverage Wald Tests of Slope Equality

*Values in parentheses are p-values associated with Wald statistics. Bootstrap variance was used for inference. Source: Author's own calculations based on data from Institut National de la Statistique (Institut National de la Statistique, 2021).

Table *6* summarizes the bootstrap inference diagnostics and overall model performance for the quantile regression estimates. The results indicate that standard errors stabilised at 1,000 replications for the central and lower quantiles. For the upper quantile ($\tau = 0.90$), where observations are relatively sparse, additional replications were examined to verify robustness. No substantial changes in standard errors were observed beyond 1,000 iterations, which indicate that the chosen number of bootstrap replications is sufficient to ensure stable and reliable inference across all quantiles. Bootstrap standard errors are larger than the analytical standard errors for both coverage schemes. This pattern indicates that conventional asymptotic variance estimates may underestimate the true sampling variability of the coefficients, particularly in the presence of heteroskedasticity, skewed expenditure distributions, and potential model misspecification. The use of bootstrap-based inference therefore provides more reliable statistical inference within the quantile regression framework. The proportion of statistically significant coefficients increases markedly at the upper quantile ($\tau = 0.90$), reaching 78% for CNAM and 89% for AMEN beneficiaries. This pattern reflects the fact that explanatory variables exert stronger effects in the upper tail of the OOPE distribution, where high-cost health episodes occur and where catastrophic expenditure risk is concentrated. The results therefore confirm the importance of modelling the full conditional distribution of health expenditures rather than relying solely on mean-based approaches. Diagnostic tests also indicate strong model stability. No quantile crossing is detected across the estimated conditional quantiles, confirming the internal consistency and monotonic ordering of the estimated quantile process. This supports the robustness of the model specification and the validity of the estimated distributional effects.

The pseudo-R^2 values increase steadily across quantiles for both insurance schemes, rising from 0.20 to 0.38 for CNAM and from 0.24 to 0.45 for AMEN. This progression indicates that the explanatory variables account for a larger share of variation in higher expenditure levels, where health shocks, socioeconomic vulnerability, and geographic access constraints exert stronger influence. The more pronounced increase in pseudo-R^2 among AMEN beneficiaries suggests that structural determinants play a particularly important role in shaping extreme OOPE outcomes among socially vulnerable households.

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	CNAM	AMEN
Bootstrap replications	1,000	1,000
Mean bootstrap SE	86.4	112.7
Median bootstrap SE	74.2	98.5
% Significant at 5% ($\tau = 0.90$)	78%	89%
Quantile crossing detected?	No	No
Pseudo-R^2 ($\tau = 0.25$)	0.20	0.24
Pseudo-R^2 ($\tau = 0.50$)	0.26	0.31
Pseudo-R^2 ($\tau = 0.75$)	0.32	0.38
Pseudo-R^2 ($\tau = 0.90$)	0.38	0.45
Mean analytical SE	71.5	90.3
Mean bootstrap SE	86.4	112.7
% Difference (Bootstrap vs. Analytical)	+20.8	+24.8

TABLE 6: Bootstrap Inference and Model Diagnostics

Source: Author's own calculations based on data from Institut National de la Statistique (Institut National de la Statistique, 2021).

Discussion

This study provides new evidence on the determinants of OOPE within Tunisia's social health coverage system by examining how financial exposure varies across the expenditure distribution and between coverage schemes. The findings indicate that financial protection remains uneven despite the expansion of social health coverage. Structural factors, particularly health needs, socioeconomic vulnerability, and geographic access constraints, play a decisive role in shaping household financial risk, especially in the upper tail of the expenditure distribution where catastrophic spending occurs.

Health needs emerge as the most important determinant of financial exposure. Chronic disease and disability significantly increase the likelihood of high OOPE, particularly at higher expenditure quantiles. This pattern reflects the growing financial implications of the epidemiological transition toward noncommunicable diseases (NCDs), which increasingly dominate the disease burden in Tunisia (Rejaibi et al., 2022) and across the EMR countries (Iqbal et al., 2024). Similar findings have been documented in multiple middle-income countries, where households affected by chronic diseases experience significantly higher risks of CHE despite the presence of social health insurance systems (Chowdhury et al., 2025). In Tunisia, previous studies have also highlighted the increasing financial burden associated with chronic

diseases and long-term treatment needs (Abu-Zaineh et al., 2013) and (Ismaïl and Arfa, 2022). The persistence of this relationship suggests that existing coverage arrangements do not fully protect households from the costs associated with long-term care, medicines, and repeated medical consultations.

Socioeconomic inequalities remain another important source of financial vulnerability. Lower levels of education and larger household size are associated with higher OOPE, particularly among beneficiaries of the AMEN program. These results are consistent with international evidence showing that poorer households remain disproportionately exposed to healthcare costs even in systems where publicly funded coverage schemes exist (Bhatia et al., 2022). Similar patterns have been observed in Morocco (Hassani et al., 2025), Egypt (Rashad and Sharaf, 2015), and Tunisia (Ismaïl and Arfa, 2022), where publicly subsidized coverage programs have improved access to care but have not fully eliminated the financial burden associated with medicines, diagnostics, and specialized services. In Tunisia, socioeconomic disparities in healthcare utilization and financial exposure have also been documented in national health surveys and studies examining equity in access to care.

Geographic disparities in healthcare provision represent another structural determinant of financial exposure. The association between distance to tertiary hospitals and higher OOPE highlights the role of territorial inequalities in shaping financial protection outcomes. Tunisia's health system is characterized by a concentration of specialized services in urban areas, particularly in the coastal regions (Arfa and Achouri, 2008). This spatial imbalance forces households living in interior regions to incur additional travel and service costs when seeking specialized care. Evidence from North African health systems suggests that such territorial inequalities often translate into higher household expenditures and delayed access to treatment (Katoue et al., 2022). These structural imbalances should be addressed to improve both financial protection and equitable access to care.

The comparison between CNAM and AMEN beneficiaries further illustrates the difference between nominal coverage and effective financial protection. Although both schemes are designed to provide financial risk pooling, the results indicate that AMEN beneficiaries remain more exposed to high expenditure episodes, particularly in response to chronic illness and geographic barriers to care. Similar segmentation effects have been documented in several countries where contributory and subsidized coverage schemes coexist. Evidence from Iran (Doshmangir et al., 2021), Indonesia (Shrestha, 2021), and Turkey (Tirgil et al., 2019) and Thailand (Tangcharoensathien et al., 2019) suggests that targeted social assistance programs often expand coverage among vulnerable populations but may offer shallower financial protection due to limitations in benefit packages or service availability. These experiences highlight the broader challenge of ensuring that coverage expansion translates into effective protection against financial hardship.

The findings have important implications for health policy in Tunisia. First, strengthening financial protection for chronic disease management should represent a central priority. Expanding access to essential medicines, diagnostic services, and outpatient care for NCDs could significantly reduce the concentration of OOPE in the upper tail of the expenditure distribution. International experience shows that strong primary healthcare systems and integrated chronic disease management programs play a crucial role in improving the financial protection (Erlangga et al., 2019). Second, improving territorial equity in healthcare provision is essential. Expanding the availability of specialized in underserved regions, strengthening referral systems, and developing telemedicine or decentralized diagnostic services could help reduce the financial burden associated with centralized tertiary care (Cao et al., 2025). Such reforms are particularly important in countries where regional disparities in healthcare infrastructure contribute to unequal access to treatment. Third, strengthening the financial protection mechanisms of the AMEN program should be considered a priority. Although the program plays a critical role in expanding coverage for vulnerable populations, the results suggest that its ability to protect beneficiaries from high-cost health events remains limited. Policy options could include expanding the depth of coverage for specialized care, strengthening reimbursement mechanisms, or introducing explicit protection against CHE.

Fourth, the study highlights the importance of distribution-sensitive approaches in evaluating health financing policies. Traditional mean-based indicators may underestimate the financial risks faced by households experiencing severe health shocks. Quantile-based methods provide a more comprehensive understanding of how financial protection mechanisms

operate across different segments of the expenditure distribution and are therefore particularly useful for identifying vulnerabilities associated with catastrophic health spending.

Tunisia has an advanced system of social health coverage; however, the effective financial protection remains only partially fulfilled. For a long time, the expansion of coverage has been viewed mainly as a technical achievement rather than as a social contract intended to shield households from the silent diseases-related financial hardship. An integrated reforms that combine unification of risk pooling CNAM and AMEN and geographic healthcare access improvement. The unified pooling could be supported by designing an essential benefits package that strengthen primary health care and access to essential medicines, while the Ministry of Health ensures a more balanced distribution of health infrastructure and workforce across regions. Such reforms are essential for translating progress toward UHC into real reductions in household financial hardship.

Limitations and future research

The study is subject to limitations. First, the cross-sectional design constrains causal inference and may introduce selection bias when comparing CNAM and AMEN households, as these groups differ structurally. Future research should therefore rely on longitudinal or panel data and apply causal inference methods (e.g., instrumental variables) to better identify cause-effect relationships and reduce selection bias. Second, while censored quantile regression effectively captures distributional heterogeneity, it does not explicitly model the joint decision-making process underlying healthcare utilization and expenditure intensity. Further work could address this limitation by employing two-part, hurdle, or structural models to jointly analyze access to care and spending behavior. Finally, the measurement of OOPE is based on self-reported survey data, which may be affected by recall bias and reporting errors. Future studies should aim to integrate administrative data sources or improved survey instruments to enhance the accuracy and reliability of expenditure estimates.

Conclusions

This study shows that OOPE within Tunisia's social health coverage system is highly heterogeneous across the expenditure distribution and between coverage schemes. Chronic disease and disability are the main drivers of high OOPE, with stronger effects in the upper tail where catastrophic spending risk is concentrated. Socioeconomic disadvantage and geographic barriers further increase financial vulnerability, particularly through low education levels, larger household size, distance to tertiary hospitals, and reliance on specialized care.

The comparison between CNAM and AMEN highlights a clear gap between nominal coverage and effective financial protection. Although both schemes provide risk pooling, AMEN households remain more exposed to severe health shocks and access-related constraints, particularly at higher expenditure levels. These findings suggest that expanding coverage alone is insufficient. Unifying risk pooling between CNAM and AMEN could strengthen risk equalization and expand financial resources. Combined with the development of an essential benefits package and a more balanced distribution of health workforce and infrastructure, such reforms could improve access to primary care and essential medicines, enhance geographic equity in healthcare provision, and ultimately translate the expansion of social coverage into more effective financial protection.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Chokri Arfa

Acquisition, analysis, or interpretation of data: Chokri Arfa

Drafting of the manuscript: Chokri Arfa

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Critical review of the manuscript for important intellectual content: Chokri Arfa

Supervision: Chokri Arfa

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The data supporting this study are openly available in the Institut National de la Statistique (Tunisia) at the following link: https://www.ins.tn/enquetes/enquete-nationale-sur-le-budget-la-consommation-et-le-niveau-de-vie-des-menages-2021

References

1. Abdelaziz AB, Haj Amor S, Ayadi I, Khelil M, Zoghlami C, Ben Abdelfattah S: Financing health care in Tunisia. Current state of health care expenditure and socialization prospects, on the road to Universal Health Coverage. La Tunisie Medicale. 2018, 96:789-807.
2. Abu-Zaineh M, Arfa C, Ventelou B, Ben Romdhane H, Moatti JP: Fairness in healthcare finance and delivery: what about Tunisia?. Health Policy and Planning. 2014, 29:433-442. 10.1093/heapol/czt029
3. Abu-Zaineh M, Ben Romdhane H, Ventelou B, Moatti JP, Chokri A: Appraising financial protection in health: the case of Tunisia. International Journal of Health Care Finance and Economics. 2013, 13:73-93. 10.1007/s10754-013-9123-8
4. Arfa, C, & Achouri, H: Tunisia: good practice in expanding health care coverage. Lessons from reforms in a country in transition. The World Bank, 2008.
5. Bhatia D, Mishra S, Kirubarajan A, Yanful B, Allin S, Di Ruggiero E: Identifying priorities for research on financial risk protection to achieve universal health coverage: a scoping overview of reviews. BMJ Open. 2022, 12:e052041. 10.1136/bmjopen-2021-052041
6. Cao X, Li G, Zhao H: Can telemedicine help integrate the referral-based healthcare system? An economic and operational analysis. PloS one. 2025, 20:e0336490. 10.1371/journal.pone.0336490
7. Chernozhukov V, Hong H: Three-step censored quantile regression and extramarital affairs. Journal of the American Statistical Association. 2002, 97:872-882. 10.1198/016214502388618663
8. Che Ramli AAB, Kim YJ: Quantile regression model for interval-censored data with competing risks. Journal of Applied Statistics. 2025, 52:2438-2447. 10.1080/02664763.2025.2474627
9. Chowdhury NMRA, Urme SA, Hridoy A, Nusrat F, Miah MS: Exploring the effects catastrophic health expenditure due to non-communicable diseases and coping strategies: A case study among households in Bangladesh. Public Health in Practice. 2025, 10:100642. 10.1016/j.puhip.2025.100642
10. Cylus J, Thomson S, Evetovits T: Catastrophic health spending in Europe: equity and policy implications of different calculation methods. Bulletin of the World Health Organization. 2018, 96:599-609. 10.2471/blt.18.209031
11. Chen S, Wang Q: Quantile regression with censoring and sample selection. Journal of Econometrics. 2023, 234:205-226. 10.1016/j.jeconom.2021.11.018
12. Doshmangir L, Bazyar M, Rashidian A, Gordeev VS: Iran health insurance system in transition: equity concerns and steps to achieve universal health coverage. International Journal for Equity in Health. 2021, 20:37. 10.1186/s12939-020-01372-4
13. Endalamaw A, Mengistu TS, Khatri RB, Wolka E, Erku D, Zewdie A, Assefa Y: Universal health coverage-Exploring the what, how, and why using realist review. PLOS Global Public Health. 2025, 5:e0003330. 10.1371/journal.pgph.0003330

14. Erlangga D, Suhrcke M, Ali S, Bloor K: The impact of public health insurance on health care utilisation, financial protection and health status in low- and middle-income countries: A systematic review. Plos one. 2019, 14:e0219731. 10.1371/journal.pone.0219731

15. Eze P, Lawani LO, Aguc UJ, Acharya Y: Catastrophic health expenditure in sub-Saharan Africa: systematic review and meta-analysis. Bulletin of the World Health Organization. 2022, 100:337-351J. 10.2471/blt.21.287673

16. Hassani A, Bakhat M, Boudhar A: The incidence of catastrophic and impoverishing health spending in Morocco: the value added of new methodologies. International Journal of Health Economics and Management. 2025, 25:337-382. 10.1007/s10754-025-09397-4

17. Hsu J, Flores G, Evans D, Mills A, Hanson K: Measuring financial protection against catastrophic health expenditures: methodological challenges for global monitoring. International Journal for Equity in Health. 2018, 17:69. 10.1186/s12939-018-0749-5

18. Institut National de la Statistique: Enquête Nationale sur le Budget, la Consommation et le Niveau de Vie des Ménages. Tunisie. 2021,

19. Iqbal M, Iqbal R, Siddiqi S, et al.: Engagement of private healthcare sector in addressing noncommunicable diseases at primary care level in the Eastern Mediterranean Region. Eastern Mediterranean Health Journal. 2024, 30:333-343. 10.26719/2024.30.5.333

20. Ismaïl S, Arfa C: Effects of out-of-pocket medicine's spending on catastrophic expenditure and impoverishment in Tunisia. Value in Health Regional Issues. 2022, 30:109-118. 10.1016/j.vhri.2022.01.008

21. Jiang R, Qian W, Zhou Z: Variable selection and coefficient estimation via composite quantile regression with randomly censored data. Statistics & Probability Letters. 2012, 82:308-317. 10.1016/j.spl.2011.10.017

22. Kansra P, Oberoi S, Garg A: Out-of-pocket payments & catastrophic healthcare expenditure for non-communicable diseases: Results of a State-wide STEPS survey in north India. The Indian Journal of Medical Research . 2025, 161:229-238. 10.25259/ijmr_625_2024

23. Katoue MG, Cerda AA, García LY, Jakovljevic M: Healthcare system development in the Middle East and North Africa region: Challenges, endeavors and prospective opportunities. Frontiers in Public Health. 2022, 10:1045739. 10.3389/fpubh.2022.1045739

24. Koenker R, Bassett JG: Regression quantiles. Econometrica. 1978, 46:33-50. 10.2307/1913643

25. Koenker R, Machado JA: Goodness of fit and related inference processes for quantile regression. Journal of the American Statistical Association. 1999, 94:1296-1310. 10.1080/01621459.1999.10473882

26. Kwon KN, Chung W: Effects of private health insurance on medical expenditure and health service utilization in South Korea: a quantile regression analysis. BMC Health Services Research. 2023, 23:1219. 10.1186/s12913-023-10251-x

27. Liu C, Chhabra KR, Scott JW: Catastrophic health expenditures across insurance types and incomes before and after the patient protection and affordable care act. JAMA Network Open. 2020. 3:e2017696. 10.1001/jamanetworkopen.2020.17696

28. Nasri K, Amara M, Helmi I: The landscape of social protection in Tunisia. Economic Research Forum [Working Paper No, 1592]. 2022,

29. Nguyen HA, Ahmed S, Turner HC: Overview of the main methods used for estimating catastrophic health expenditure. Cost Effectiveness and Resource Allocation. 2023, 21:50. 10.1186/s12962-023-00457-5

30. Panda HS, Rout HS, Jakovljevic M: Catastrophic health expenditure of inpatients in emerging economies: evidence from the Indian subcontinent. Health Research Policy and Systems. 2024, 22:104. 10.1186/s12961-024-01202-x

31. Rashad AS, Sharaf MF: Catastrophic and impoverishing effects of out-of-pocket health expenditure: new evidence from Egypt. American Journal of Economics. 2015, 5:526-533.

32. Rejaibi S, Zoghalami N, Silini A, et al.: Leading causes of death in Tunisia, 2020. European Journal of Public Health. 2022, 32:10.1093/eurpub/ckac131.218

33. Shrestha R: Health Insurance for the poor, healthcare use and health outcomes in Indonesia. Bulletin of Indonesian Economic Studies. 2021, 57:85-110. 10.1080/00074918.2020.1753655

34. Söyük S: The impact of public health expenditure and gross domestic product per capita on the risk of catastrophic health expenditures for OECD countries. Frontiers in Public Health. 2023, 11:1122424. 10.3389/fpubh.2023.1122424

35. StataCorp. (2021). https://www.stata.com/stata17/.

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36. Tangcharoensathien V, Patcharanarumol W, Kulthanmanusorn A, Saengruang N, Kosiyaporn H: The political economy of UHC reform in Thailand: lessons for low-and middle-income countries. Health Systems & Reform. 2019, 5:195-208. 10.1080/23288604.2019.1630595

37. Thomson S, Cylus J, Evetovits T: Can people afford to pay for health care? New evidence on financial protection in Europe. World Health Organization, 2019.

38. Tirgil A, Dickens WT, Atun R: Effects of expanding a non-contributory health insurance scheme on out-of-pocket healthcare spending by the poor in Turkey. BMJ Global Health. 2019, 4:e001540. 10.1136/bmjgh-2019-001540

39. United Nations: Classification of individual consumption according to purpose (COICOP). 2018.

40. Wagstaff A, van Doorslaer E: Catastrophe and impoverishment in paying for health care: with applications to Vietnam 1993-1998. Health Economics. 2003, 12:921-933. 10.1002/hec.776

41. Whiting K: Progress has slowed on universal health coverage: Here's what needs to happen. World Economic Forum. 2023,

42. World Health Organization: Global monitoring report on financial protection in health 2021. World Health Organization, 2021.

43. World Health Organization: Tracking universal health coverage: 2023 global monitoring report. World Health Organization, 2023.

44. World Health Organization. (2025). Accessed: December 2025: https://apps.who.int/nha/database/.

45. Xu K, Evans DB, Carrin G, Aguilar-Rivera AM: Designing health financing systems to reduce catastrophic health expenditure. World Health Organization, 1-4; 2005.

46. Xu K, Evans DB, Kawabata K, Zeramdini R, Klavus J, Murray CJL: Household catastrophic health expenditure: a multicountry analysis. The Lancet. 2003, 362:111-117. 10.1016/S0140-6736(03)13861-5

47. Zhang T, Kato K, Ruppert D: Bootstrap inference for quantile-based modal regression. Journal of the American Statistical Association. 2021, 118:122-134. 10.1080/01621459.2021.1918130

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