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**Geographical disparities in adult obesity prevalence: small-area analysis
of the Chilean National Health Surveys**

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Abstract

Background

Previous representative health surveys conducted in Chile evidenced a high obesity prevalence rate among adults, especially in female and urban areas. Nevertheless, these have limited utility for targeted interventions and local source allocation for prevention. This study analyzes the increments in adult obesity prevalence rates and the geographic variation at the regional level. We also assessed whether the obesity rates have different patterns on a smaller geographic level than national and regional ones.

Methods

This ecological study analyzed data from two representative national samples of adults ≥ 18 years old, who participated in the last Chilean health surveys, 2009 ($n=5,412$) and 2016 ($n=6,233$). Obesity (body mass index ≥ 30 Kg/m²) rates were calculated on the national, regional, and Health Service (HS) levels, being HS the smallest unit of analysis available. Obesity rates and relative increase to early identify target populations and geographic areas, with 95% confidence intervals (95% CI), were calculated using the sampling design of the national surveys, at the national and regional level, and by gender, age groups, and socioeconomic status. The Fay-Herriot (FH) models, using auxiliary data, were fitted for obesity rates estimates at the HS level.

Results

The relative increase of obesity rate was 37.1% (95%CI 23.3-52.9) at the national level, with a heterogeneous geographic distribution at the regional one. Southern Regions had the

highest obesity rates in both surveys (Aysén: 35.2%, 95%CI 26.9-43.5 in 2009, 44.3% 95%CI 37-51.7 in 2016), but higher increases were predominantly in the northern and central areas of the country (relative increase 91.1% 95%CI 39.6-110.1 in Valparaiso and 81.6 95%CI 14.4-196.2 in Tarapacá). Obesity rates were higher in females, older age, and lower socioeconomic groups; nevertheless, relative increases were higher in the opposite ones. The Fay-Herriot estimates showed an obesity rates variation at the HS level, where higher rates tend to converge to specific HS areas of each Region.

Conclusion

Adult obesity rates and relative increase are diverse across subnational levels and substantially differ from the national estimates, highlighting a pattern that converges to areas with medium-low-income households. Our results emphasize geographical disparities in obesity prevalence among adults.

Keywords: obesity, small-area analysis, geographic variation, medium-low-income households.

Introduction

Halting the increase of obesity prevalence is an ever-pressing issue for Public Health policymakers. The worldwide rate of obesity has trebled over the past four decades, reaching 650 million (13%) and 1.9 billion (39%) obese and overweight adults in 2016, accounting for more deaths than undernutrition. This problem is more challenging in middle-low income countries due to the fact that the rapid upsurge of obesity coexists with undernutrition, while resources to deal with both are scarce (1,2).

National Health Surveys (NHS) and complex surveillance systems are the usual frameworks to quantify the burden of diseases for planning interventions and resource allocation. Nevertheless, surveillance systems are seldom available in lower-middle-income countries. Moreover, the NHS is not updated as fast as needed and only represents large geographical areas (e.g., national and urban-rural levels). On the other hand, national-level or large geographical area estimates do not account for the disease variability in smaller geographical areas within a country, potentially missing information and target populations. For example, emerging evidence reported substantial geographical disparities in childhood mortality, cardiovascular and suicide rates (3–5), infectious diseases (6–8), and in healthcare costs (9,10) at subnational levels, highlighting the importance of geographic variation and the fast-growing demand for reliable small-area estimates. Concerning obesity, some studies based on NHS and surveillance records found a substantial difference in the small-area pattern of obesity rates among adults in high-income countries (11–16) and in children (17–19). Since these studies cross-sectionally estimate obesity rates in smaller areas (20,21), there is a gap of knowledge of the increase of obesity rate among adults, especially in a setting where medium-low income households persist.

81 Chile can be a benchmark for anticipating the course and prevention policies of obesity in
82 medium-low income settings, due to the country has experienced the fastest nutritional
83 transition during the last four decades, tracking from high rates of undernutrition in the
84 1960s to high rates of obesity in the 2000s (22). According to the World Bank, Chile
85 experienced the fastest growing economy in Latin America in recent decades; nevertheless,
86 has substantial socioeconomic variability. So that Regions and Communes (the second and
87 third geographic administrative divisions, respectively) of lower-middle-income persist
88 (23). The last Chilean NHS reported that the obesity prevalence was 31% in 2016, affecting
89 predominantly women and urban areas, with no examination of regional variation of the
90 increase of obesity rates or the potential influence of smaller geographic areas.

91 The main objective of this study was to analyze the geographic variation of the increase of
92 the obesity prevalence rates among adults at the national and regional levels, which are
93 appropriate and valid for inference, comparing data from two representative NHS from
94 Chile. Secondly, we assessed the geographic variation of the obesity rate on a smaller
95 geographical unit related to health care services distribution, using small-area estimations
96 (SAE).

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Method

Design and data

We did a secondary analysis study based on the Chilean National Health Surveys (NHS) dataset. These datasets are held by the Subsecretaria de Salud Pública del Ministerio de Salud de Chile and are anonymized and freely available by request at

<https://www.portaltransparencia.cl/>. Consequently, this study did not require ethical approval, consent to participate, and other administrative permission. All methods were carried out in accordance Declaration of Helsinki and Chilean regulations.

Chile is geographically divided into three administrative levels: Regions (15 regions until 2017), Provinces (56 provinces), and Communes (346). On the other hand, Chile conducted three National Health Surveys (NHS). The last two NHS (NHS-2009 and NHS-2016) were considered for our analysis because sampling designs are similar; nevertheless, there are some differences in measured health conditions or risk factors. NSH-2009 and NSH-2016 are probabilistic samples of the general population aged 15 and over, with national and regional representativeness. The NHS's four-stage sampling design includes a random sampling of Communes, census zones, households, and individuals stratified by gender and urban-rural areas.

NHS-2009 was carried out between October 2009 and September 2010 and covered thirteen health conditions and other selected risk factors (alcohol, tobacco, food and salt consumption, passive exposure to environmental tobacco smoke). The participation rate was 85%; 5412 subjects completed the questionnaires and had clinical examinations,

Field Code Changed

including laboratory tests and anthropometric measurements. The NHS-2016, developed between August 2016 to March 2017, extended its measures to 60 health conditions, including risk factors and population health determinants. The participation rate was 90%, 6233 subjects completed the health questionnaires, and 5220 had clinical and laboratory tests and anthropometry. In both surveys, health questionnaires, clinical examinations, and measured height (in centimeters) and weight (in kilograms) data were completed by trained nurses and study staff visiting each selected household and following standardized procedures and validated instruments/equipment. The variables analyzed were weight, height, gender, age, education level, the Region of residence, and the individual's health care system, including the health services (HS) records explained later. Only complete data from both surveys were included in our analysis.

Definition of obesity and subnational geographic levels

We used the World Health Organization's criteria to define adult obesity: body mass index (BMI) over or equal to 30 Kg/m². We calculated BMI as weight/height².

Chilean NHS has national, regional, gender, and urban/rural areas representativeness but does not collect representative data at the country's second and third geographic administrative division (provinces and commune). Each participant's commune or province of residence is not wholly and reliably registered either. Instead, we constructed a smaller geographical area using ancillary data recorded on both NHS, indirectly related to the commune or province, the Health Services (HS). The health system in Chile is based on 29 sub-regional geographical HS, which aim to manage and develop a public healthcare network under a defined jurisdiction, being different between them in terms of geographical area extension, population density, educational levels, and family income. In this way, we

analyzed obesity prevalences rates at three geographical levels: national, regional, and HS areas, being the last one the smallest unit of analysis available.

By the time of NHS (2016-2017), Chile was administratively divided into 15 Regions from north to south. Regions are grouped only for the interpretative purpose by the following macro zones: North zone, Central zone, Central-south, South, and Austral zone.

Data processing

All analysis accounted for the complex sampling design to produce population-based weighted nationally representativeness according to Chilean NSH analytic guidelines.

At the national and regional levels, we calculated obesity prevalence rates (obesity rate from now on) with 95% confidence intervals (95% CI) using the sampling expansion factors (Chilean NSH guidelines); we named this as the traditional approach (TA). To estimate the absolute (difference between obesity rate in NHS2016 and NHS2009) and relative increase rates (ratio between difference and obesity rate in NHS2009) and their 95% CI, we fitted linear regression and log-linear models; both models consider the probabilities of inclusion of each survey. These rates were also calculated for the following subpopulation: gender (male, female), age groups (15-24y, 25-44y, 45-64y 65y or more), and education level as a socioeconomic status proxy variable (low, medium, high). Due to Chile already having elevated obesity rates (NSH-2016), we emphasize the relative increase indicator, rather than the absolute one, to identify target areas or subgroups for early prevention since this indicator depends on its baseline value.

For SAE at the HS level, we used Fay-Herriot (FH) models for the obesity rates estimations. We preferred FH from other emerging SAE models because it is a well-known

lineal-mixed-model approach to fill the data gap over small geographic areas. It accounts for too small sample sizes and provides accurate direct estimates (24). Two types of models were fitted:

FS model:

$$\hat{\delta}_d^{DIR} = \delta_d + e_d, e_d \sim N(0, \psi_d), \text{ and } d = 1, \dots, D$$

$$\delta_d = x_d^T \beta + u_d, \text{ where } u_d \sim N(0, A), \text{ and } d = 1, \dots, D$$

Where δ_d is the parameter to be estimated in the area d ($d = 1, \dots, D$). $\hat{\delta}_d^{DIR}$ is the unbiased directed estimator (DIR) obtained with the sample design. ψ_d is the sample variance of the direct estimator in each area. x_d^T are the auxiliary linear predictors related to variables of interest, and A is a matrix $D \times D$, where D is the geographic unit or area of analysis.

SFH model is the spatial Fay-Herriot model (SFH) to reduce estimation variance at under sampled areas and spatial autocorrelation due to neighborhood distance, which assumes that $u = (u_1, \dots, u_D)$ related to the areas that follow a first-order autoregressive process SAR(1). That is:

$$u = \rho_1 W u + \epsilon, \text{ where } \epsilon \sim N(0_D, \sigma_1^2 I_D).$$

Where 0_D is a vector of zeros, and I_D the identity matrix. W is the proximity matrix $D \times D$ obtained by a row standardization of an initial matrix with zeros and ones, where the number 1 indicates if the areas are neighbors. ρ_1 is a scalar parameter.

The area-level auxiliary data and covariates used for SAE were children obesity/overweight and mortality rates at the commune level, population size, and the number of medical establishments at the HS level. These data are public and accessible in Chile (25).

Direct (DIR), FS, and SFH estimates with standard errors (SE) were reported. DIR is calculated using data exclusively from the NHS and is similar to the obesity rate with TA. We fitted log-linear models and the FH and SFH modes for the relative increase in HS areas, and later FH and SFH models were fitted.

Graphs and maps to show geographic variation were also constructed for results visualization. All the analyses were conducted in R version 4.1.1 (26). Figures and maps are produced using R packages *ggplot* (version 3.3.5), *ggrepel* (version 0.9.1[23]), *rgdal* (version 1.5-23), *rgeos* (version 0.5-5), and *chilemapas* (versión 0.2). Obesity rates were calculated using the package *survey* (version 4.1-1), and FH models were estimated using package *SAE* version 1.3.

Results

A total of 4884 (90.2%) and 5220 (83.7%) complete registers of NSH-2009 and NSH-2016, respectively, were analyzed in this study. Sample size distribution by the regional level and regions aggregated by macro zones are displayed in table 1. Chile has 15 Regions with 29 HS imbalanced distributed across each Region. For instance, the Valparaíso, Metropolitan, Biobío, La Araucanía, and Los Lagos Regions have from 2 to 6 HS areas; in contrast, there is just one HS for the rest of the Regions (Table 1).

208 **Table 1. Health Service areas and sample size distribution by Chilean Regions and**
209 **macro zones.**

Macro zone	Regions*	NHS-2009	NHS-2016	HS
North	Arica y Parinacota	290	303	1. Arica
	Tarapacá	279	285	2. Iquique
	Antofagasta	290	272	3. Antofagasta
	Atacama	291	281	4. Atacama
Central	Coquimbo	287	293	5. Coquimbo
	Valparaíso	316	580	6. Valparaíso San Antonio 7. Viña del Mar Quillota 8. Aconcagua
	Metropolitana	817	832	9. M. Norte 10. M. Occidente 11. M. Central 12. M. Oriente 13. M. Sur 14. M. Suroriente
	L. Bdo. O'Higgins	309	292	15. O'Higgins
Central-south	Maule	329	340	16. Del Maule
	Biobío	263	601	17. Ñuble 18. Concepción 19. Talcahuano 20. Biobío 21. Arauco
	La Araucanía	291	273	22. Araucanía norte 23. Araucanía sur
South	Los Ríos	286	289	24. Valdivia
	Los Lagos	288	297	25. Osorno 26. Reloncavi 27. Chiloe

Austral	Aysén	252	307	28. Aysén
	Magallanes	297	275	29. Magallanes

NHS: National Health Survey. HS: Health Service

* Regions are ordered according to their geographic location, from north to south.

Table 2 shows the sample size distribution by the subpopulations of the study. In NSH-2009, 59.7% of the sample were female, 24.7% older than 65 years, and 26.6% low socioeconomic status. While 63.4% were female, 24.7% older than 65 years, and 22.3% had low socioeconomic status in the NSH-2016 (Table 2).

Table 2. Sample size distribution by subpopulations in NHS-2009 and NHS-2016, Chile

	NHS-2009	NHS-2016
Gender		
Male	1966 (40.3)	2019 (36.6)
Female	2918 (59.7)	3501 (63.4)
Age groups		
15 to 24 y	727 (14.9)	729 (13.2)
25 to 44 y	1613 (33.0)	1571 (28.5)
45 to 64 y	1611 (33.0)	1857 (33.6)
65 y or more	933 (19.1)	1363 (24.7)
Socioeconomic status		
Low	1297 (26.6)	1229 (22.3)
Medium	2658 (54.4)	2948 (53.4)
High	912 (18.7)	1196 (21.7)
Total	4884	5520

NHS: National Health Survey. HS: Health Service

Obesity rates, absolute and relative increase at regional levels and by subpopulations

At the national level, the adult obesity rates in the NHS-2009 and NSH-2016 were 25.1% (95%CI 23.0-27.2) and 34.4% (95%CI 32.1-36.8), respectively, representing a significant relative increase of 37.1% (95%CI 23.3-52.9). Figure 1 is the map of Chile where Regions are geographically displayed from north to south and obesity rates with 95%CI, showing the heterogeneous geographic distribution of obesity rates in both surveys regarding the regional level. The highest obesity rates were concentrated in the country's southern regions in both surveys; meanwhile, in regions from the north and center zones of the country, obesity rates oscillate around or lower than the national average in both surveys (Figure 1A and 1B). Table 4 of supplemental material contains the obesity rates, absolute and relative increase with 95%CI at national and regional levels. (Supplement, table 4).

Figure 1. Distribution of the obesity rates in National Health Survey 2009 (A), 2016 (B) by Regions, Chile.

A) NHS-2009*

B) NHS-2016

Obesity rates and 95%CI are illustrated as proportions
NSH: National Health Survey. 95%CI: 95% Confidence Intervals.
*Regions are geographically displayed from north to south. The vertical dashed line represents the obesity rate at the national level.

Figure 2 illustrates the obesity relative increase rates by Regions, meaning the reference line no increments. There is also a geographical variation in obesity relative increase rates; however, this is predominantly in the northern and central zones of the country (Figure 2). The highest obesity relative increase was observable in Tarapacá (81.6, 95%CI 11.4-196.2) and Valparaíso (91.1%, 95%CI 39.6-116.6). Moreover, three regions from the central and central-south macron zones had a significant relative increase: Coquimbo (50.1%, 95%CI 7.3-110.1), Biobío (49.8%, 95%CI 8.6-106.6), and Metropolitan Region (33.8%, 95%CI 7.6-66.4) (Figure 2). These results and the absolute increase are detailed in the supplementary material (supplement, table 4).

Figure 2. Adult obesity prevalence relative increase rate from NHS-2009 to NHS-16 at the regional level, Chile.

Obesity relative increase rates and 95%CI are illustrated as proportions
 NSH: National Health Survey. 95%CI: 95% Confidence Intervals.
 *Regions are geographically displayed from north to south. The vertical dashed line
 represents the obesity rate at the national level.

Regarding subpopulations, the female obesity rate was higher than males in both surveys;
 nevertheless, obesity relative increase in males was higher than in females (57.0%, 95%CI
 31.5-87.4 vs. 25.7%, 95%CI 10.7-42.7). Similarly, obesity rates were higher in older age
 groups, but relative increases were higher in the younger ones (62.4%, 95%CI 11.9-135.6;
 53.2% 95%CI 26.9-85.0 vs. 19.1%, 95%CI 2.3-38.6; 14.9%, 95%CI 7.4-42.7). Educational
 level is used as a proxy for the socioeconomic status in Chilean NSH. In this sense, low and
 medium socioeconomic subgroups have higher obesity rates than their counterparts,
 although a high relative increase was observable in the high-socioeconomic group (58.7%,
 95%CI 19.4-110.9 vs. 32.8%, 95%CI 11.6-57.9 and 35.1%, 95%CI 17.7-55.1) (Tables 3).

Table 3. Adult obesity indicators by subpopulations in Chile.

	Prevalence (95% CI) NHS-2009	Prevalence (95% CI) NHS-2016	Absolute increase	Relative increase %
Gender				
Male	19.3 (16.5-22)	30.3 (27.1-33.5)	11.0 (6.8-15.2)	57.0 (31.5-87.4)
Female	30.6 (27.6-33.5)	38.4 (35.3-41.6)	7.9 (3.5-12.2)	25.7 (10.7-42.7)
Age groups				
15 to 24 y	11.0 (7.6-14.3)	17.8 (14.0-21.6)	6.8 (1.8-11.9)	62.4 (11.9-135.6)
25 to 44 y	23.6 (20.0-27.1)	36.1 (31.9-40.3)	12.5 (7.1-18.0)	53.2 (26.9-85.0)
45 to 64 y	35.4 (31.4-39.5)	42.2 (38.0-46.4)	6.8 (0.9-12.6)	19.1 (2.3-38.6)
65 y or more	31.0 (25.6-36.4)	35.6 (31.1-40.1)	4.6 (2.4-11.7)	14.9 (7.4-42.7)
Socioeconomic status				
Low	35.1 (30.6-39.6)	46.6 (41.1-52.1)	11.5 (4.4-18.6)	32.8 (11.6-57.9)
Medium	24.7 (22.2-27.3)	33.4 (30.5-36.3)	8.7 (4.7-12.6)	35.1 (17.7-55.1)
High	18.5 (14.1-22.9)	29.4 (24.8-34.1)	10.9 (4.5- 17.3.2)	58.7 (19.4-110.9)

95% CI: 95% Confidence Interval. NHS: National Health Survey

^aCalculated according to the Chilean NHS traditional approach.

^bDifference between obesity rates in NHS-2016 and NHS-2009

^cThe ratio between the difference an obesity rate in NHS-2009) $\times$ 100

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Figure 3 shows the SFH model's obesity rate estimates and 95%IC for the 29 HS areas of Chile in NHS-2009 and NHS-2016, where HS areas are displayed from north to south. A geographic variation of obesity rates at the HS level was observed in both surveys. HS areas with an obesity rate over the national average tend to converge to the country's southern zone in NHS-2009 and NHS-2016. Figure 3 also highlights how certain HS areas in the north and central Chilean macro zones also had high obesity rates according to NHS-2016.

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Figure 3. Spatial Fay-Herrot adult obesity rates estimates by Health Services areas, Chile.

A) NHS-2009

A) NHS-2016

NSH: National Health Survey. 95%CI: 95% Confidence Intervals. HS: Health Service
 *HS are geographically displayed from north to south. The vertical dashed line represents the obesity rate at the national level.

364

365 Figure 5 (supplementary material) shows that SF and SFH obesity rates estimates tend to be
366 similar to the unbiased direct estimator (Direct) in HS areas but with less variability in their
367 standard error. Table 5 (supplementary material) shows the obesity rates estimates from the
368 Direct, Fay-Herriot models, and sample size at the HS level only in Regions with two or more
369 HS areas to illustrate the variability of obesity rate within their respective Region.
370 Additionally, SF and SFH estimates tend to be similar.

371 Araucanía and Los Lagos Regions, from the south zone, had the highest obesity rates in both
372 surveys and similar in all their HS areas (supplement, table 5). The obesity rate in Valparaíso
373 Region (central zone) 2 of its 3 HS areas already had prevalence similar to the national one
374 (25.8% in San Antonio and 25.4% in Viña del Mar, 25.1% the national rate), even higher in
375 the San Antonio HS area in NSH-2016 (38.6% vs. 34.9% national rate). The Metropolitan
376 Region is one of the most populated of Chile. The obesity rates at HS areas in this Region
377 tended to be homogenous in NSH-2009; however, it is observable a major geographic
378 variation across its HS areas in NSH-2016, where the highest obesity rates concentrate in 2
379 of its 6 HS's areas (39.6% in M. Occidente and 35.5% in M. Norte). This variability at the
380 HS level was also observable in the Biobío Region from the central-south zone (Supplement,
381 Table 5).

382 Regarding to obesity relative increase at the HS level, there is also a variation between HS
383 areas belonging to the same Region; for example, in the Valparaíso region, a region with
384 the highest obesity prevalence and relative increase rates, this is concentrated in certain HS
385 areas (Figure 4).

386

Figure 4. Relative increase rate in adult obesity in Regions with two o more HS areas, Chile.

HS: Health Service. HS in Metropolitana Region: 9. M. Norte. 10. M. Occidente. 11. M. Central. 12. M. Oriente. 13. M. Sur. 14. M. Suroriente. Valparaíso Region: 6. Valparaíso San Antonio. 7. Viña del Mar Quillota. 8. Aconcagua Araucanía Region: 22. Araucanía sur. 23. Araucanía norte. Los Lagos Region: 25. Osorno. 26. Reloncaví. 27. Chiloé.

Discussion

To our knowledge, this is the first study that reported the geographic variation of obesity rate increments and obesity rates at smaller geographic areas in Chile. The main purpose of studying geographic variation in disease rates is to provide health management information and formulate hypotheses about the environmental determinants of disease. The "hot spot" can also be identified as a high concentration of cases in a particular area. Subsequently, the correlation between geographic disease variation and concomitant variation in the degree of exposure to environmental or lifestyle can be addressed (13, 24). Identifying small areas of highest prevalence allows to address the health consequences of obesity and provide specific resources to provide an early diagnosis and timely treatment. Moreover, identifying environmental drivers will promote better urban planning (28).

Chile presents a great regional variation in socio-economic development and disparities in health indicators (23). Consequently, our study's results show that the prevalence of adult obesity and its increments are very heterogeneous in the territory, even within regions. Disclosing that the "hot spots" are different between subnational levels and smaller areas, represented by Regions and the Health Services, respectively, and suggesting geographic disparities in obesity. Scrutinizing our results, health services areas with higher obesity prevalence coincide with less developed Communes in Chile according to the Community Development Indicator (CDI) (23), even into Regions with better socioeconomic development. However, this seems to be different in the relative increments.

The Metropolitan Region (the Region with the most population density), as an example, has the highest CDI (0.50), and its obesity rate is near to the national average (31.7%, NHS-2016). Nevertheless, Health Service areas belonging to less developed communes showed

higher obesity rates (HS M. Occidente: 40%, HS M. Norte 35 %), contrary to those with higher CDI (HS M. Oriente 26%). On the other hand, other HS areas have the largest relative increases (HS M. Central and HS M. Suroriente). Even though there is a knowledge gap regarding factors that could explain the observed differences, further hypotheses to be tested are the influence of socioeconomics or educational factors, and other environmental drivers of obesity. Literature also suggests access to green areas that encourage physical activity, safe public transport planning and promote joint mobility with bicycles and walks, barriers to the consumption of junk food, etc.

In addition, our findings based on the relative obesity increases indicators make visibly hidden "hot spots" susceptible to earlier preventive interventions. Male, youngest age, highest socioeconomic status, and Regions from the central and norths zone of the country are becoming the targeted groups of concern. High prevalence and the emerging relative obesity increases in other subpopulations also lead to reflection on the public policy measures taken in the country to solve or confront the problem. The establishment of laws (such as nutrition labeling), as the only measure, has been insufficient to curb obesity. The above reinforces the importance of examining prevalence at sub-national levels and the need to adjust preventive measures to the local reality to face the determinants of this problem. These can be studied using modern approaches such as big data, artificial intelligence, geo-analysis, agent-based models, and public health dashboards (29).

Strengths of our study include the large sample size, which represents adults 15 years of age and older, and the standardized weight and height measurements conducted by trained personnel in both surveys, which gives reliable indicators for comparison. Traditional and

well-known modeling for SAE allowed us to estimate obesity prevalence in smaller areas, where sample sizes are too small or insufficient. Although the above could explain high prevalence due to high variability, evidence supports the reliability of different SAE approaches; moreover, our interim analysis reinforces the robustness of our estimates (Supplement). Still, local surveillance data for direct estimation would be preferable, and local government should consider resources to better track obesity and other obesity-related chronic health conditions at this level.

The principal limitation of our study is that we have no complete data at the province or commune level. Instead, we use Health Service data as a proxy variable and the education level as a proxy socioeconomic status. Health Service data may misrepresent communes, especially in Regions with less health service access or rural areas. Nevertheless, this is the first study exploring the utility of this data and brightening to light important geographic variations in obesity prevalence among adults. In addition, due to the potential for bias, ecological studies should only be considered the first step in investigating the potential associations between environmental agents and disease geography differences (30).

In conclusion, this study determined that the adult obesity rates and relative increase at subnational levels substantially differ from the national estimates, highlighting geographical disparities in obesity prevalence among adults. These findings suggest that stakeholders should stake prevention programs and resource investment locally and evaluate determinants of these disparities and their impact on other diseases.

469 **List of abbreviation**

470	NHS	National Health Survey
471	HS	Health Service
472	BMI	Body Mass Index
473	TA	Traditional Approach
474	FH	Fay-Herriot estimates
475	SFH	Spatial Fay-Herriot estimates
476	95%CI	95% Confidence Interval
477	SE	Standard Errors

478

479 **Reference**

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Declarations

- **Ethics approval and consent to participate**

We did a secondary analysis study based on the Chilean National Health Surveys (NHS) datasets, which are anonymized and public free data. Consequently, this study did not require ethical approval and consent to participate.

- **Consent for publication**

'Not Applicable'

- **Availability of data and materials**

The data supporting this study's findings are held by the Subsecretaria de Salud Pública del Ministerio de Salud de Chile and are publicly available at request from <https://www.portaltransparencia.cl/>. However, data are available from the authors upon reasonable request and with the permission of Alejandro Sepulveda, the first author of the study.

- **Competing interests**

The authors declare no conflict of interest.

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595 • **Authors' contributions**

596 ASP contributed to the design, performed all statistical analyses, data interpretation,
597 drafted and critically revised the manuscript. FC contributed to the design, statistical
598 analyses, data interpretation and critically revised the manuscript. MG contributed
599 to the conception and data interpretation critically revised the manuscript. PM
600 contributed data interpretation critically revised the manuscript. GM contributed
601 data interpretation critically revised the manuscript. CU contributed to the
602 conception, design, and data interpretation and drafted and critically revised the
603 manuscript.

604 All authors revised the final version of the manuscript gave their final approval.

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607 .

Figures

A) NHS-2009*

B) NHS-2016

Obesity rates and 95%CI are illustrated as proportions
NSH: National Health Survey. 95%CI: 95% Confidence Intervals.
*Regions are geographically displayed from north to south. The vertical dashed line represents the obesity rate at the national level.

Figure 1

Distribution of the obesity rates in National Health Survey 2009 (A), 2016 (B) by Regions, Chile.

Figure 2

Adult obesity prevalence relative increase rate from NHS-2009 to NHS-16 at the regional level, Chile.

A) NHS-2009

B) NHS-2016

NSH: National Health Survey. 95%CI: 95% Confidence Intervals. HS: Health Service
*HS are geographically displayed from north to south. The vertical dashed line represents the obesity rate at the national level.

Figure 3

Spatial Fay-Herrot adult obesity rates estimates by Health Services areas, Chile.

Figure 4

Relative increase rate in adult obesity in Regions with two o more HS areas, Chile.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Geographicaldisparitiesinadultobesityprevalencesupplementary.doc](#)