california health interview survey

CHIS 2023 Methodology Report Series

Report 5

Weighting and Variance Estimation

February 2025

UCLA Center for Health Policy Research

CALIFORNIA HEALTH INTERVIEW SURVEY

<u>**CHIS 2023 METHODOLOGY SERIES**</u>

REPORT 5

WEIGHTING AND VARIANCE ESTIMATION

February 2025

This report was prepared for the California Health Interview Survey by Susan Sherr, Jonathan Best, Arina Goyle, Kathy Langdale and Margie Engle-Bauer of SSRS.

www.chis.ucla.edu

This report describes the weighting and variance estimation methods used in CHIS 2023. This report presents the steps used to create the analytical weights for analyzing the data from the adult, child, and adolescent interviews.

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PREFACE

Weighting and Variance Estimation is the fifth and final in a series of methodological reports describing the 2023 California Health Interview Survey (CHIS). The other reports are listed below.

CHIS is a collaborative project of the University of California, Los Angeles (UCLA) Center for Health Policy Research, the California Department of Public Health, and the Department of Health Care Services. SSRS was responsible for data collection and the preparation of five methodological reports from the 2023 survey. The survey examines public health and health care access issues in California. The survey is the largest state health survey ever undertaken in the United States.

Methodological Report Series for CHIS 2023

The methodological reports for CHIS 2023 are as follows:

- Report 1: Sample Design;
- Report 2: Data Collection Methods;
- Report 3: Data Processing Procedures;
- Report 4: Response Rates; and
- Report 5: Weighting and Variance Estimation.

The reports are interrelated and contain many references to each other. For ease of presentation, the references are simply labeled by the report numbers given above. After the Preface, each report includes an "Overview" (Chapter 1) that is nearly identical across reports, followed by detailed technical documentation on the specific topic of the report.

Report 5: Weighting and Variance Estimation (this report) describes the weighting and variance estimation methods from CHIS 2023. The purpose of weighting the survey data is to permit analysts to produce estimates of the health characteristics for the entire California population and subgroups including counties, and in some cases, cities. This report presents the steps used to create the analytical weights for analyzing the data from the adult, child, and adolescent interviews.

For further methodological details not covered in this report, refer to the other methodological reports in the series at http://chis.ucla.edu/chis/design/Pages/methodology.aspx. General information on CHIS data can be found on the California Health Interview Survey Web site at http://chis.ucla.edu or by contacting CHIS at CHIS@ucla.edu.

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1. CHIS 2023 SAMPLE DESIGN AND METHODOLOGY SUMMARY

1.1 Overview

A series of five methodology reports is available with more detail about the methods used in CHIS 2023.

- Report 1 – Sample Design;
- Report 2 – Data Collection Methods;
- Report 3 – Data Processing Procedures;
- Report 4 – Response Rates; and
- Report 5 – Weighting and Variance Estimation.

For further information on CHIS data and the methods used in the survey, visit the California Health Interview Survey Web site at http://www.chis.ucla.edu or contact CHIS at CHIS@ucla.edu. For methodology reports from previous CHIS cycles, go to https://healthpolicy.ucla.edu/our-work/california-health-interview-survey-chis/chis-design-and-methods/chis-methodology-reports-repository.

The CHIS is a population-based multimode (web and telephone) survey of California's residential, noninstitutionalized population conducted every other year since 2001 and continually beginning in 2011. CHIS is the nation's largest state-level health survey and one of the largest health surveys in the nation. The UCLA Center for Health Policy Research (UCLA-CHPR) conducts CHIS in collaboration with multiple funding sources from public, private, and non-profit organizations. CHIS collects extensive information for all age groups on health status, health conditions, health-related behaviors, health insurance coverage, access to health care services, and other health and health-related issues.

The sample is designed and optimized to meet two objectives:

1) Provide estimates for large- and medium-sized counties in the state, and for groups of the smallest counties (based on population size), and
2) Provide statewide estimates for California's overall population, its major racial and ethnic groups, as well as several racial and ethnic subgroups.

The CHIS sample is representative of California's non-institutionalized population living in households. CHIS data and results are used extensively by federal and State agencies, local public health agencies and organizations, advocacy and community organizations, other local agencies, hospitals, community clinics, health plans, foundations, and researchers. These data are used for analyses and publications to assess public health and health care needs, to develop and advocate policies to meet those needs, and to plan and budget health care coverage and services. Many researchers throughout California and the nation use CHIS data files to further their understanding of a wide range of health related issues (visit UCLA-CHPR's publication page at https://healthpolicy.ucla.edu/our-work/publications for examples of CHIS studies).

1.2 Sample Additions and Data Collection Methodology Updates

Starting in 2021, the CHIS added a prepaid cell phone sample to the primary ABS sample. A second innovation was altering the envelope for the initial mailing to have a window that would allow the incentive to be seen. The CHIS research team deemed these changes necessary to improve representation of California's diverse population and improve response rates.

For CHIS 2023, respondents in the ABS sample are invited to either complete the survey online or call in to be interviewed by a member of the SSRS interviewing staff. Respondents receive an initial invitation letter with a $2.00 pre-incentive. This is followed by a reminder postcard, a standard letter, and a final postcard. Where addresses can be matched to a listed telephone number, the nonresponding households are also called up to six times to attempt to complete an interview before the sampled household is considered to be a resolved nonresponse. In addition to the ABS sample frame, CHIS 2023 utilized a supplemental listed prepaid cell phone sample to meet targets in certain stratum.

The prepaid cell phone oversample followed the same dialing protocol of up to six dials before retiring the sample. In addition, the sampled phone number was screened for respondents who were either aged 18 to 24, Hispanic, African American, or would take the survey in one of the non-English languages offered for CHIS 2023.

In addition to the prepaid cell phone oversample, CHIS 2023 included two geographic oversamples:

1) An oversample of households from 11 ZIP codes in the City of Long Beach.
2) An oversample of households in Santa Clara County.

In order to provide CHIS data users with more complete and up-to-date information to facilitate analyses of CHIS data, additional information on how to use the CHIS sampling weights, including sample statistical code, is available at https://healthpolicy.ucla.edu/our-work/california-health-interview-survey-chis/access-chis-data/resources .

Additional documentation on constructing the CHIS sampling weights is available in the *CHIS 2023 Methodology Series: Report 5—Weighting and Variance Estimation* posted at https://healthpolicy.ucla.edu/our-work/california-health-interview-survey-chis/chis-design-and-methods/chis-methodology-reports-repository. Other helpful information for understanding the CHIS sample design and data collection processing can be found in the four other methodology reports for each CHIS cycle and year.

1.3 Sample Design Objectives

The CHIS 2023 sample was designed to meet the two sampling objectives discussed above: (1) provide estimates for adults in most counties and in groups of counties with small populations; and (2) provide estimates for California's overall population, major racial and ethnic groups, and for several smaller racial and ethnic subgroups.

To achieve these objectives, CHIS 2023 continued to employ an address-based sample design. For the ABS sample, the 58 counties in the state were grouped into 44 primary geographic sampling strata, and 14 sub-strata were created within the two most populous counties in the state (Los Angeles and San Diego). The same geographic stratification of the state has been used since CHIS 2005. The Los Angeles County stratum included eight sub-strata for Service Planning Areas, and the San Diego County stratum included six sub-strata for Health Service Districts. Most of the strata (39 of 44) consisted of a single county with no sub-strata (see counties 3-41 in Table 1-1). Three multi-county strata comprised the 17 remaining counties (see counties 42-44 in Table 1-1). A sufficient number of adult interviews were allocated to each stratum and sub-stratum to support the first sample design objective for the two-year cycle—to provide health estimates for adults at the local level.

As with CHIS 2021-2022, the address-based sample in CHIS 2023 was stratified into different strata that had higher incidences of individuals with targeted characteristics. For CHIS 2023, these strata were based on predictive models that employed Big Data techniques to identify household attributes such as demographics, spoken languages, and even attitudinal metrics that are correlated with important respondent characteristics. The process begins by taking prior data and building models with those data, and then scoring future samples with the outcomes of those models. In addition to evaluating the predictive models, for CHIS 2023 we also investigated the utility of individual sample flags provided by MSG database information, including the surname flags, child indicator variables, and resident age information as well as PDB block-group characteristics including the density of households with African American residents and households with limited English proficiency.

For CHIS 2023, the following strata were created[1]:

1) Vietnamese
2) Korean
3) Likely Asian-language Interview
4) Likely Spanish-language interview
5) Hispanic
6) Other high-density non-English
7) Other Asian
8) High density African American
9) HH with children
10) Other 65+
11) Residual - Match
12) Residual – No match

This stratification scheme was designed to make use of the most effective predictive variables to target key demographic subgroups in an efficient way that minimizes the impact of the disproportionate sampling on the design effect. Those models that were not sufficiently predictive to add value were excluded. It should be noted that this stratification includes two additional strata: 1) sample records for which none of the variables or models predicted any attribute, but for which auxiliary data could be matched to the address ("Residual - Match" sample) and sample for which no Big Data was found ("Residual - No match" sample). The final step in utilizing the models is to develop sampling fractions by which modeled households will be selected. The final sample fractions balanced the need to increase the frequency of the lowest incidence groups, while accounting for subgroup differences in response propensity and minimizing disproportionate weighting whenever possible.

Within each geographic and modeled stratum combination, residential addresses were selected, and within each household, one adult (age 18 and over) respondent was randomly selected. In those households with adolescents (ages 12-17) and/or children (under age 12), one adolescent and one child of the selected parent/guardian were randomly selected. The adolescent was interviewed directly via CATI or Web. The child interview was completed by the selected adult respondent who was the parent or guardian.

[1] The Santa Clara oversample employs a slightly different strata, please refer to Methodology Report 1 – Sample Design for additional details.

Table 1-1. California county and county group strata used in the CHIS 2023 sample design

1. Los Angeles	7. Alameda	27. Shasta
1.1 Antelope Valley	8. Sacramento	28. Yolo
1.2 San Fernando Valley	9. Contra Costa	29. El Dorado
1.3 San Gabriel Valley	10. Fresno	30. Imperial
1.4 Metro	11. San Francisco	31. Napa
1.5 West	12. Ventura	32. Kings
1.6 South	13. San Mateo	33. Madera
1.7 East	14. Kern	34. Monterey
1.8 South Bay	15. San Joaquin	35. Humboldt
2. San Diego	16. Sonoma	36. Nevada
2.1 N. Coastal	17. Stanislaus	37. Mendocino
2.2 N. Central	18. Santa Barbara	38. Sutter
2.3 Central	19. Solano	39. Yuba
2.4 South	20. Tulare	40. Lake
2.5 East	21. Santa Cruz	41. San Benito
2.6 N. Inland	22. Marin	42. Colusa, Glenn, Tehama
3. Orange	23. San Luis Obispo	43. Del Norte, Lassen, Modoc, Plumas, Sierra, Siskiyou, Trinity
4. Santa Clara	24. Placer	
5. San Bernardino	25. Merced	44. Amador, Alpine, Calaveras, Inyo, Mariposa, Mono, Tuolumne
6. Riverside	26. Butte	

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

In addition to the ABS sample frame, CHIS 2023 utilized a supplemental listed prepaid cellphone sample to meet targets in twelve geographic stratum that were underperforming in completion rate. Listed prepaid cell phones were sampled from the following 12 geographic strata:

1. Los Angeles
    a. SPA1
    b. SPA5
2. San Diego
    a. Central
3. Santa Clara
4. Sacramento

5. Contra Costa
6. Ventura
7. San Joaquin
8. Sonoma
9. Santa Cruz
10. Merced
11. Mendocino
12. San Benito

To better target populations not adequately covered under the ABS frame in CHIS 2023, we utilized a prepaid cell phone oversample of 450 completes to obtain additional in-language interviews, Hispanic and African American samples, and young adults. Prepaid cell phone numbers are associated with cell phones that are "pay-as-you-go" and do not require a contract. Prepaid numbers are more likely to be used by Hispanics, people with lower education and lower income, and other related groups that are often underrepresented in general population samples (e.g., the uninsured)

The CHIS ABS sample and the prepaid oversample were of sufficient size to accomplish the second objective, i.e., to produce statistically stable estimates for small population groups such as racial/ethnic subgroups, children, adolescents, etc.

1.4 Data Collection

To capture the rich diversity of the California population, interviews were conducted in six languages: English, Spanish, Chinese (Mandarin and Cantonese dialect), Vietnamese, Korean, and Tagalog. These languages were chosen based on analysis of ACS 2021 5-year data to identify the languages that would cover the largest number of Californians in the CHIS sample that either did not speak English or did not speak English well enough to otherwise participate.

SSRS collaborated with UCLA on the methodology and collected data for CHIS 2023, under contract with the UCLA Center for Health Policy Research. SSRS is an independent research firm that specializes in innovative methodologies, optimized sample designs, and reaching low-incidence populations. For all sampled households, one randomly selected adult in each sampled household either completed an on-line survey or was interviewed by telephone by an SSRS interviewer. In addition, the study sampled one adolescent and one child if they were present in the household and the sampled adult was their parent or legal guardian. Thus, up to three interviews could have been completed in each household. The child interview was moved in 2019 to take place immediately after Section A of the adult survey and the rostering of the household. The adolescent survey took place either immediately after the adult with phone interviews or in a separate session online.

Table 1-2 shows the number of completed adult, child, and adolescent interviews in CHIS 2023 by mode of interview. Note that these figures were accurate as of data collection completion for 2023 and may differ slightly from numbers in the data files due to data cleaning and edits. Sample sizes to compare against data files you are using are found online at [https://healthpolicy.ucla.edu/our-work/california-health-interview-survey-chis/chis-design-and-methods/chis-design.](https://healthpolicy.ucla.edu/our-work/california-health-interview-survey-chis/chis-design-and-methods/chis-design)

Table 1-2. Number of completed interviews by mode of interview and instrument

	Adult	Child	Adolescent
Totals[1]	23,697	3,650	1,045
Completes by Web	21,101	3,370	989
Completes by phone	2,596	280	56

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.
[1] Includes interviews meeting the criteria of sufficient partial.

Interviews in all languages were administered using SSRS's computer-assisted web interviewing and computer-assisted telephone interviewing (CAWI/CATI) system. As expected, the CATI interviews were longer in duration. The duration of the CATI interviews averaged almost 68 minutes, 20 minutes, and 25 minutes for the adult, child, and adolescent interviews, respectively; the duration of the CAWI interviews averaged around 45 minutes, 13 minutes, and 18 minutes for the adult, child, and adolescent interviews, respectively. Interviews in non-English languages typically took longer to complete across both modes: the non-English CATI interviews had an average length of about 76 minutes, 22 minutes, and 25 minutes for the adult, child, and adolescent interviews respectively; the non-English CAWI interviews had an average length of about 54 minutes, 16 minutes, and 18 minutes for the adult, child, and adolescent interviews, respectively.

Nearly 8 percent of the adult interviews were completed in a language other than English, as were about 12 percent of all child (parent proxy) interviews and 2 percent of all adolescent interviews.

Table 1-3 shows the major topic areas for each of the three survey instruments (adult, child, and adolescent). If questions were asked in only one year of survey implementation, the specific year is indicated in the table.

Table 1-3. CHIS 2023 survey topic areas by instrument

Health status	**Adult**	**Adolescent**	**Child**
General health status	✓	✓	✓
Days missed from work or school due to health problems	✓	✓	✓
Health conditions	**Adult**	**Adolescent**	**Child**
Asthma	✓	✓	✓
Diabetes	✓		
Heart disease, High blood pressure, Cholesterol	✓		
Physical disability	✓		
Mental health	**Adult**	**Adolescent**	**Child**
Mental health status	✓	✓	
Perceived need, Access and utilization of mental health services	✓	✓	
Functional impairment, Stigma	✓		
Suicide ideation and attempts	✓	✓	
Telehealth and mental health services satisfaction, Delays in mental health services	✓	✓	
Climate Change	✓	✓	
Health behaviors	**Adult**	**Adolescent**	**Child**
Moderate physical activity	✓		
Dietary intake	✓	✓	✓
Breastfeeding (younger than 3 years)			✓
Sugar-sweetened beverages	✓	✓	✓
Alcohol use, Cigarette use, E-cigarette use, Marijuana use, CBD use	✓	✓	
CBD Use	✓		
Opioid use, Prescription painkiller use	✓		
Exposure to second-hand smoke/vapor, Exposure to marijuana smoke	✓		
Sexual behaviors, HIV testing, HIV prevention medication	✓	✓	
Caregiving	✓		
Gambling, Financial and mental impacts of gambling	✓		
Gun Violence	**Adult**	**Adolescent**	**Child**
Firearm ownership/presence, Loaded, and secure, Firearm victimization, Quick access to firearm	✓		
Women's health	**Adult**	**Adolescent**	**Child**
Pregnancy status	✓		

(continued)

Table 1-3. CHIS 2023 survey topic areas by instrument (continued)

Dental health	**Adult**	**Adolescent**	**Child**
Last dental visit, Main reason have not visited dentist, Number of dental visits, Location of dental service	✓	✓	✓
Current dental insurance coverage	✓	✓	✓
Source of dental care	✓	✓	✓
Neighborhood and housing	**Adult**	**Adolescent**	**Child**
Safety, Social cohesion	✓	✓	✓
Civic engagement	✓	✓	
Participation in extracurricular activities		✓	
Housing security/stability, Place of residency last year	✓		
Encounters with police	✓		
Adverse Childhood Experiences	**Adult**	**Adolescent**	**Child**
ACES Screener	✓	✓	
Past ACES screener	✓	✓	
Safe and nurtured childhood experiences	✓	✓	
Access to and use of health care	**Adult**	**Adolescent**	**Child**
Usual source of care, Visits to medical doctor	✓	✓	✓
Emergency room visits	✓	✓	✓
Delays in getting care (prescriptions and medical care)	✓	✓	✓
Communication problems with doctor	✓		✓
Contraception	✓	✓	
Timely appointment	✓	✓	✓
Access to specialist and general doctors	✓		
Telehealth care, Telehealth visit satisfaction and barriers	✓		
Care coordination	✓	✓	✓
Discrimination in healthcare setting	✓		
Difficulty in accessing care, tests, treatment	✓	✓	✓
Voter engagement	**Adult**	**Adolescent**	**Child**
Voter engagement	✓		
Voter attitudes	✓		
Food environment	**Adult**	**Adolescent**	**Child**
Availability of food in household over past 12 months, Hunger	✓		

(continued)

Table 1-3. CHIS 2023 survey topic areas by instrument (continued)

Health insurance	**Adult**	**Adolescent**	**Child**
Current insurance coverage, Spouse's coverage, Who pays for coverage	✓	✓	✓
Health plan enrollment, Characteristics and assessment of plan	✓	✓	✓
Whether employer offers coverage, Respondent/spouse eligibility	✓		
Coverage over past 12 months, Reasons for lack of insurance	✓	✓	✓
High deductible health plans	✓	✓	✓
Partial scope Medi-Cal, Medical debt, Hospitalizations	✓		
Public program eligibility	**Adult**	**Adolescent**	**Child**
Household poverty level	✓		
Program participation (CalWORKs, Food Stamps, SSI, SSDI, WIC, TANF)	✓	✓	✓
Assets, Child support, Social security/pension, Worker's compensation	✓		
Medi-Cal eligibility, Medi-Cal renewal, Notice of actions from Medi-Cal	✓		
Reason for Medi-Cal non-participation among potential beneficiaries	✓	✓	✓
Use of public benefits among immigrant residents	✓		
Parental involvement/adult supervision	**Adult**	**Adolescent**	**Child**
Parental involvement			✓
Book ownership, Source of reading materials, Challenges to reading to child			✓
Child care and school	**Adult**	**Adolescent**	**Child**
Current child care arrangements			✓
Paid child care	✓		
First 5 California: Talk, Read, Sing Program / Kit for New Parents			✓
Preschool/school attendance, School name		✓	✓
Preschool quality			✓
Employment	**Adult**	**Adolescent**	**Child**
Employment status, Spouse's employment status	✓		
Hours worked at all jobs	✓		
Industry and occupation, Firm size	✓		
Paid Family Leave	✓		
Income	**Adult**	**Adolescent**	**Child**
Respondent's and spouse's earnings last month before taxes	✓		
Household income, Number of persons supported by household income	✓		

(continued)

Table 1-3. CHIS 2023 survey topic areas by instrument (continued)

Respondent characteristics	Adult	Adolescent	Child
Race and ethnicity, Age, Gender, Height, Weight	✓	✓	✓
Veteran status	✓		
Marital status, Registered domestic partner status (same-sex couples)	✓		
Sexual orientation	✓		
Gender identity	✓	✓	
Gender expression		✓	
Living with parents	✓		
Education, English language proficiency	✓		
Citizenship, Immigration status, Country of birth, Length of time in U.S., Languages spoken at home	✓	✓	✓
COVID-19	**Adult**	**Adolescent**	**Child**
Ever tested positive for COVID-19, Test type	✓		
Experienced long COVID-19 symptoms	✓		
COVID vaccine status, COVID booster status	✓	✓	✓
Future COVID vaccine acceptance, Reasons for COVID vaccine hesitancy	✓		
Challenges experience due to COVID-19 pandemic	✓		
N95 masks, Ability to get N95 masks	✓		
Adolescent Future Preparedness	**Adult**	**Adolescent**	**Child**
Plans for college, Impact of pandemic on college plans		✓	
Discrimination	**Adult**	**Adolescent**	**Child**
Housing discrimination experience, Main reason for discrimination, Housing Choice Section 8 Voucher	✓		
Hate incident experience and witness, Type, Location, Reason for hate incident	✓	✓	

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

1.5 Response Rates

The overall response rates for CHIS 2023 are composites of the screener completion rate (i.e., success in introducing the survey to a household and randomly selecting an adult to be interviewed) and the extended interview completion rate (i.e., success in getting one or more selected persons to complete the extended interview). For CHIS 2023, the overall household response rate was 8.5 percent (the product of the screener response rate of 11.8 percent and the extended interview response rate at the household level of 72.1 percent). CHIS uses the RR4 type response rate described in the AAPOR (The American Association for Public Opinion Research), 2016 guidelines (see more detailed in *CHIS 2023 Methodology Series: Report 4 – Response Rates*).

The extended interview response rate for the ABS sample varied across the adult (64.7 percent), child (82.2 percent) and adolescent (27.9 percent) interviews. The adolescent rate includes the process of obtaining permission from a parent or guardian.

Multiplying these rates by the screener response rates used in the household rates above gives an overall response rate for each type of interview for 2023 (see Table 1-4b).

Table 1-4a. CHIS response rates - Conditional

Type of Sample	Screener[1]	Household (given screened)[1]	Adult (given screened)[1]	Child (given screened & eligibility)[1]	Adolescent (given screened & permission)[1]
Overall	11.8%	72.1%	64.7%	82.2%	27.9%

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] The prepaid cell, Long Beach, and Santa Clara oversamples are not included in these rates.

Table 1-4b. CHIS response rates - Unconditional

Type of Sample	Screener[1]	Household (given screened)[1]	Adult (given screened)[1]	Child (given screened & eligibility)[1]	Adolescent (given screened & permission)[1]
Overall	11.8%	8.5%	7.7%	9.7%	3.3%

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] The prepaid cell, Long Beach, and Santa Clara oversamples are not included in these rates.

After all follow-up attempts to complete the full questionnaire were exhausted, adults who completed at least approximately 80 percent of the questionnaire (i.e., through Section K which covers employment, income, poverty status, and food security), were counted as "sufficient partial complete." At least some responses in the employment and income series, or public program eligibility and food insecurity series were missing from those cases that did not complete the entire interview. They were imputed to enhance the analytic utility of the data.

Proxy interviews were conducted for any adult who was unable to complete the extended adult interview for themselves, in order to avoid biases for health estimates of chronically ill or handicapped people. Eligible selected persons were re-contacted and offered a proxy option. In CHIS 2023, either a spouse/partner or adult child completed a proxy interview for sixteen adults. A reduced questionnaire, with questions identified as appropriate for a proxy respondent, was administered.

Further information about CHIS data quality and nonresponse bias is available at https://healthpolicy.ucla.edu/our-work/california-health-interview-survey-chis/chis-design-and-methods/chis-design/chis-2019-2020-redesign.

1.6 Weighting the Sample

To produce population estimates from CHIS data, weights were applied to the sample data to compensate for the probability of selection and a variety of other factors, some directly resulting from the design and administration of the survey. The sample was weighted to represent the noninstitutionalized population for each sampling stratum and statewide. The weighting procedures used for CHIS 2023 accomplish the following objectives:

- Compensate for differential probabilities of selection for addresses (households) and persons within household;
- Reduce biases occurring because non-respondents may have different characteristics than respondents;
- Adjust, to the extent possible, for under coverage in the sampling frame and in the conduct of the survey; and
- Reduce the variance of the estimates by using auxiliary information

As part of the weighting process, a household weight was created for all households that completed the screener interview. This household weight is the product of the "base weight" (the inverse of the probability of selection of the address) and several adjustment factors. The household weight was used to compute a person-level weight, which includes adjustments for the within-household sampling of persons and for nonresponse. The final step was to adjust the person-level weight using weight calibration, a procedure that forced the CHIS weights to sum to estimated population control totals simultaneously from an independent data source (see below).

Population control totals of the number of persons by age, race, and sex at the stratum level for CHIS 2023 were primarily created from the California Department of Finance's (DOF) 2023 Population Estimates, and associated population projections. The procedure used several dimensions, which are combinations of demographic variables (age, sex, race, and ethnicity), geographic variables (county, Service Planning Area) in Los Angeles County, and Health and Human Services Agency (HHSA) region in San Diego County), and education. One limitation of using DOF data is that it includes about 2.4 percent of the population of California who live in "group quarters" (i.e., persons living with nine or more unrelated persons and includes, for example nursing homes, prisons, dormitories, etc.). These persons were excluded from the CHIS target population and, as a result, the number of persons living in group quarters was estimated and removed from the DOF control totals prior to calibration.

The DOF control totals used to create the CHIS 2023 weights are based on 2020 Census counts. Please pay close attention when comparing estimates using CHIS 2023 data with estimates using data from CHIS cycles before 2023. The most accurate California population figures are available when the U.S. Census Bureau conducts the decennial census. For periods between each census, population-based surveys like CHIS must use population projections based on the decennial count. For example, population control totals for CHIS 2009 were based on 2009 DOF estimates and projections, which were based on Census 2000 counts with adjustments for demographic changes within the state between 2000 and 2009. These estimates become less accurate and more dependent on the models underlying the adjustments over time. Using the most recent Census population count information to create control totals for weighting produces the most statistically accurate population estimates for the current cycle, but it may produce unexpected increases or decreases in some survey estimates when comparing survey cycles that use 2010 Census-based information and 2020 Census-based information.

1.7 Imputation Methods

Missing values in the CHIS data files were replaced through imputation for nearly every variable. This was a substantial task designed to enhance the analytic utility of the files. SSRS imputed missing values for those variables used in the weighting process and UCLA-CHPR staff imputed values for nearly every other variable.

Three different imputation procedures were used by SSRS to fill in missing responses for items essential for weighting the data. The first imputation technique was a completely random selection from the observed distribution of respondents. This method was used only for a few variables when the percentage of the items missing was very small. The second technique was hot-deck imputation. The hot-deck approach is one of the most used methods for assigning values for missing responses. Using a hot deck, a value reported by a respondent for a specific item was assigned or donated to a "similar" person who did not respond to that item. The characteristics defining "similar" vary for different variables. To carry out hot-deck imputation, the respondents who answered a survey item formed a pool of donors, while the item non-respondents formed a group of recipients. A recipient was matched to the subset pool of donors based on household and individual characteristics. A value for the recipient was then randomly imputed from one of the donors in the pool. SSRS used hot-deck imputation to impute the same items that have been imputed in all CHIS cycles since 2003 (i.e., race, ethnicity, home ownership, and education). The last technique was external data assignment. This method was used for geocoding variables such as strata, Los Angeles SPA, San Diego HSSA region, and zipcode where the respondent provided inconsistent information. For such cases geocoding information was used for imputation.

UCLA-CHPR imputed missing values for nearly every variable in the data files other than those imputed by SSRS and some sensitive variables for which nonresponse had its own meaning. Overall, item nonresponse rates in CHIS 2023 were low, with most variables missing valid responses for less than 1% of the sample. Questions that go to fewer overall respondents or that ask about more sensitive topics can have higher nonresponse.

The imputation process conducted by UCLA-CHPR started with data editing, sometimes referred to as logical or relational imputation: for any missing value, a valid replacement value was sought based on known values of other variables of the same respondent or other sample(s) from the same household. For the remaining missing values, model-based hot-deck imputation without donor replacement was used. This method replaced a missing value for one respondent using a valid response from another respondent with similar characteristics as defined by a generalized linear model with a set of control variables (predictors). The link function of the model corresponded to the nature of the variable being imputed (e.g. linear regression for continues variables, logistic regression for binary variables, etc.). Donors and recipients were grouped based on their predicted values from the model.

Control variables (predictors) used in the model to form donor pools for hot-decking always included standard measures of demographic and socioeconomic characteristics, as well as geographic region; however, the full set of control variables varies depending on which variable is being imputed.

Most imputation models included additional characteristics, such as health status or access to care, which are used to improve the quality of the donor-recipient match.

Among the standard list of control variables, gender, age, race/ethnicity, educational attainment and region of California were imputed by SSRS. UCLA-CHPR began their imputation process by imputing household income so that this characteristic was available for the imputation of other variables. Sometimes CHIS collects bracketed information about the range in which the respondent's value falls when the respondent will not or cannot report an exact amount. Household income, for example, was imputed using the hot-deck method within ranges defined by a set of auxiliary variables such as bracketed income range and/or poverty level.

The imputation order of the other variables generally followed the questionnaire. After all imputation procedures were complete, every step in the data quality control process was performed once again to ensure consistency between the imputed and non-imputed values on a case-by-case basis.

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2. WEIGHTING ADJUSTMENTS

Researchers apply analysis weights to survey responses to produce estimates for the target population. The weights are designed to produce estimates with minimal biases and maximal precision (i.e., relatively small standard errors). This section provides an overview of the weighting methodology used for the CHIS 2023 one-year weights.

Specifically, the approach to weighting CHIS data is provided in Section 2.1. Base weights and adjustments are combined to form the CHIS analysis weights. The weight components are listed in Section 2.2, along with a link to the section of this report where details are provided. This chapter concludes in Section 2.3 with a brief discussion of quality assurance procedures.

2.1 Weighting Approach

The weighting approach used for CHIS 2023 follows the paradigm set in prior rounds of the study. Specifically, the methods to construct the weights follow standard design-based techniques. The use of multiple frames—landline, cell, and surname— was used consistently from CHIS 2009 - 2018 to ensure coverage of the residential California population with ABS samples used occasionally to reach specific small geographies (e.g., North Imperial county). Starting with CHIS 2019, multiple address-based samples (ABS) have been used for the sample. In 2021, a prepaid cell phone (PPD) oversample was added.

The weighting procedures described in this report resulted in a set of unified analysis weights applicable for all analyses. For example, these weights are used to generate estimates at the state-level as well as sub-state estimates at the county level.

One set of weights was produced for all CHIS person-level interviews: adult, child and adolescent. Each weight was constructed to address the following nuances of the design and data collection actualities attributed to each interview:

- Differential selection probabilities of sampled households across design strata, and for persons within the selected households;
- Reduce bias that may occur in the estimates when nonrespondents differ from their respondent counterparts;
- Reduce coverage bias associated with differences of the respondent distributions from the intended target population; and

- Improve the precision of CHIS estimates (i.e., small standard errors) by adjusting to population information and adjusting any outlier weights.

An overview of the specific weight components is provided in Section 2.2

As discussed in Chapter 9, estimates for the target population are produced only if analyses account for the CHIS sampling design and the weights. Ignoring either the sampling design or the analysis weights is not recommended.

2.2 Weighting Adjustments

CHIS one-year analysis weights were developed for adult, child and adolescent completed interviews. The weights were constructed as a function of an initial base weight (inverse selection probability within design stratum) multiplied by a sequential series of adjustments to address nonresponse, subsampling, unknown eligibility, overlapping sampling frames, and differential coverage from the intended target population. The adjustments are summarized in Section 2.2.1, followed by a comparison of the nonresponse adjustment methods used prior to 2015 and since 2015 (Section 2.2.2).

2.2.1 Components of the CHIS Analysis Weights

Details of the one-year weight components are provided in Chapters 3 through 6, beginning with the household weight (Chapter 3).

The weight associated with the selected household was derived as the product of the following components:

- base weights defined by design stratum (Section 3.1)
- residential status adjustment for household eligibility (Section 3.2)
- adjustment for nonresponse to the CHIS household screener (Section 3.3)
- calibration to Census Planning Database Low Response Score (Section 3.4)

The final household weight was used as the basis for three analysis weights (adult, child and adolescent) corresponding to extended interviews. The adult analysis weight (Chapter 4) was constructed as the final household weight multiplied by the following adjustments:

- inverse selection probability of one adult within each household with a completed screener (Section 4.1)
- adjustment for adult nonresponse (Section 4.2)

- adjustment for compositing of multiple sample frames (Section 4.3)
- pre-calibration trimming (Section 4.4)
- adjustment to align the weight sums to adult population counts by geographic area within California, demographic characteristics, and other such information (Section 4.5)

Like the adult weights, the child analysis weights (Chapter 5) were constructed as the final household weight multiplied by the following adjustments:

- adjustment to account for differing probabilities of selection based on the number of adults, parents and children in the household as well as the age of the children (Section 5.1)
- adjustment for child nonresponse (Section 5.2)
- adjustment for compositing of multiple sample frames (Section 5.3)
- pre-calibration trimming (Section 5.4)
- adjustment to align the weight sums to child population counts by geographic area within California, demographic characteristics, and other such information (Section 5.5)

The adolescent analysis weights (Chapter 6) were constructed in a similar fashion as the product of the final household weight and the following adjustments:

- adjustment to account for differing probabilities of selection based on the number of adults, parents and teens in the household with a completed screener (Section 6.1)
- adjustment for nonresponse linked to the parental permission or to the adolescent (Section 6.2)
- adjustment for compositing of multiple sample frames (Section 6.3)
- pre-calibration trimming (Section 6.4)
- adjustment to align the weight sums to adolescent population counts by geographic area within California, demographic characteristics, and other such information (Section 6.5)

A calibration adjustment (Kott, 2006; Valliant et al., 2013), such as those discussed for the adult weights in Sections 4.4, was applied to align the CHIS weights to population counts, also referred to as calibration controls or control totals. Because control totals for the CHIS target population by key covariates (e.g., design stratum) did not exist, the population counts needed to be estimated from existing information. The procedures to calculate the estimated control totals followed those used in prior rounds of CHIS and are detailed in Chapter 7.

Analysis weights address bias associated with unit nonresponse that occurs when a sample member either declines to participate or when they do not provide sufficient information for analyses. A CHIS sample member needed to complete the interview at least through the end of Section K to be classified as a respondent. Some respondents, however, declined to provide information to critical items needed for the creation of the analysis weights. This missing information was supplied through various imputation procedures detailed in Chapter 8 after the data were processed (see *CHIS 2023 Methodology Series: Report 3 - Data Processing Procedures*).

Chapter 9 contains a discussion on variance estimation for CHIS 2023. This includes Taylor Series linearization calculated with a single set of analysis weights, and Jackknife variance estimation calculated with a series of (replicate) weights. Software to calculate estimated standard errors are also discussed.

This report contains two supplementary appendices. Appendix A consists of a series of tables with frame counts, sample sizes, and base weights by the design strata. Appendix B provides summary statistics for each component discussed above.

2.2.2 Raking vs. Model-based adjustments for Nonresponse

Prior to CHIS 2015, a weighting class adjustment, much like those discussed previously, was used to account for screener and extended-interview nonresponse. Weighting classes (i.e., groups) were formed by combining binary, categorical, or categorized continuous variables thought to be associated with response and preferably also with characteristics of importance from the study. As noted in Kim et al., (2007), use of many variables can result in too many or even small (empty) weighting classes that hinder the calculation of an efficient nonresponse-adjusted weight. Determining an effective mechanism for collapsing small cells can be a time-consuming process, yielding minimal gains in precision (via reduced variations in weights) and possibly limiting the reduction of bias attributable to nonresponse. Consequently, incorporating only a few variables limits the capacity to reduce nonresponse bias, the true goal of this weight adjustment. Therefore, starting in CHIS 2015, a model-based approach was implemented with the SUDAAN® WTADJUST procedure (RTI, 2012).

2.3 Quality Checks

A series of quality control procedures was implemented at each step to ensure the accuracy of survey weights. A few examples are provided below.

First, the weight sums by stratum were compared before and after each adjustment, and after all the weighting steps, against external counts such as those tabulated from the American Community Survey (ACS). Large differences would have indicated either errors or potential problems in model-based adjustments.

Statistics of the weights (e.g., variance, minimum, maximum, unequal weighting effect) were compared before and after an adjustment. Large differences have signaled a need for further review. For example, a large relative change in an unequal weighting effect (UWE; i.e., design effect associated with the weights) calculated by important domains (e.g., race/ethnicity or geographic location) would be evaluated to determine if additional variables should be used for the weight-adjustment model or if WTADJUST bounds on the adjustments should be tightened.

The weights were also examined for outliers (see, e.g., Chen et al., 2014). Outliers were subject to trimming only after a thorough review of the weight components.

At each stage of the weighting process, sums of the replicate weights (Chapter 9) were compared against the corresponding value for the linear weights; this step ensured that approximately half of the replicate values were at or below the linear value. Estimated standard errors using linear and replicate weights were evaluated where large differences would require further evaluation of both sets of weights.

3. HOUSEHOLD WEIGHTING

The first stage of selection for CHIS 2023 as in prior years was the household by way of a sampled address from an address-based sample (ABS). Additional details on the CHIS sample design is available in *CHIS 2023 Methodology Series: Report 1—Sample Design*.

Weights generated at this stage in the process are called "household weights" to keep with the historic CHIS label. These weights by themselves, however, should not be used to generate estimates for the household population in California. Primarily, they do not incorporate important adjustment factors related to nonresponse within the household nor calibration to the number of households by county.

In this chapter, we detail the steps used to calculate the household-level weight which is used as the basis for the person-level analysis weights—adult, child (proxy), and adolescent—discussed in the subsequent chapters of this report.

Specifically, we define the initial base weight in Section 3.1 that accounts for sampling at the household level. Section 3.2 contains an adjustment for unknown residential status and non-residential address. Weights for those with unknown residential status were then set to zero. Next, we applied an adjustment for household-level nonresponse defined as households without a completed screener (Section 3.3). The final adjustment in the household weighting was to calibrate to the low response score from the Census Planning Database (Section 3.4). The final household weight is defined in Section 3.5.

Frame size, sample size and base weight by sampling frame and design stratum are provided in Appendix A. Statistics for the adjustments and the final weight are provided in Table B-1 in Appendix B.

3.1 Base Weights

A base weight, also referred to as a "design weight" or "sampling weight", adjusts only for the specific process of sampling from the sampling frame. The base weight was calculated as the inverse of the selection probability for each sampled unit from its frame. Base weights were computed for each sample separately. The base weight (BW_{ghi}) for each piece of sample i drawn from stratum h of sample frame g is computed as:

$$BW_{ghi} = \frac{N_{gh}}{n_{gh}} \tag{3.1}$$

where N_{gh} is the total number of records in stratum h of frame g and n_{gh} is the amount of sample drawn from stratum h from frame g.

3.2 Residential Status Adjustment

Sample units[2] with unknown residential status are those that cannot be classified as either residential or not residential (for ABS) or working or not working (for prepaid cell) at the end of data collection. They are units where no contact was ever made with a household member and no information was provided by the post office or gathered during dialing as to whether the unit was eligible for the survey.

The proportion of eligible sample units (p_{eli}) was computed following the AAPOR recommendation as the proportion of the resolved or observed sample units that are eligible. Since units are sampled with different selection probabilities, the base-weighted number of cases rather than the unweighted number of cases was be used to compute p_{eli}. Different values of p_{eli} were computed for each of the samples. For the address-based samples, p_{eli} was computed within strata defined by urban status and whether there was a telephone number appended to the sample. For the prepaid cell sample, p_{eli} was computed separately for cases with differing amounts of appended supplemental information including marital status, education, household income, dwelling type, own/rent and ethnic group. For the Long Beach city oversample, p_{eli} was computed overall.

The values of p_{eli} are outlined in the following table. All sampled addresses were sent to have telephone numbers appended. Of all the addresses sampled from the main ABS frame, 62 percent had a telephone number appended, either landline or cell, and of the addresses sampled from the Long Beach city oversample, 62.5 percent had a telephone number appended. These cases were eligible to be called for non-response follow-up. Thus, the final residential status for each piece of sample was based on either [a] the final postal code if no phone number was appended or the phone number was never dialed or [b] the final call disposition if a phone number was appended and that number was dialed. Table 3.1 shows p_{eli} by urban status and phone append status.

[2] Sample units are either addresses or telephone numbers depending on the sample frame.

Table 3.1. p_{eli} by urban status and phone append status

Sample Frame	Urban status (ABS) / Number of appended variables (PPD)	Phone Append	No Phone Append
Main ABS	Center city of and MSA	0.982	0.771
	Outside center city of MSA but in county of center city	0.985	0.765
	Inside suburban county of MSA	0.984	0.817
	MSA with no center city	0.982	0.758
	Not in an MSA	0.980	0.693
Long Beach City Oversample		0.983	0.783
Prepaid Cell Phone	No appended variables	0.990	NA
	One appended variable	0.990	NA
	Two appended variables	0.989	NA
	Three appended variables	0.992	NA
	Four appended variables	0.990	NA
	Five appended variables	0.989	NA
	Six appended variables	0.989	NA

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

The unknown eligibility adjusted weight, $HHA1W_i$, is the product of the base weight and an unknown eligibility adjustment:

$$HHA1W_i = HHA1F_i \times BW_i. \tag{3.2}$$

The unknown eligibility adjustment, $HHA1F_i$, is computed as follows:

$$HHA1F_i = \begin{cases} \left(\sum_{i \in ELI} BW_i + \sum_{i \in UNK\_ELI} p_{eli} \times BW_i\right) / \sum_{i \in ELI} BW_i, & \text{if } i \in \text{ELI} \\ 1, & \text{if } i \in \text{NON\_ELI} \\ 0, & i \in \text{UNK\_ELI} \end{cases} \tag{3.3}$$

where ELI denotes sample identified as eligible, NON_ELI denotes ineligible sample units, and UNK_ELI denotes sample with unknown eligibility status. BW_i is the base weight described in Section 3.1 and p_{eli} is the proportion of eligible sample units.

3.3 Household Nonresponse Adjustment

In this step, the household weights were adjusted to account for households that did not complete the household screener.

This weight, $HHA2W_i$, is computed as:

$$HHA2W_i = HHA2F_i \times HHA1W_i \tag{3.4}$$

where $HHA2F_i$ is the household nonresponse adjustment factor computed as follows:

$$HHA2F_i = \begin{cases} \left(\left(\sum_{i \in HR} HHA1W_i \right) + \left(\sum_{i \in HNR} p2_{eli} \times HHA1W_i \right) \right) \times \delta_i(c) \Big/ \sum_{i \in HR} HHA1W_i \times \delta_i(c), & \text{if } i \in \text{HR} \\ 0, & \text{if } i \in \text{HNR} \end{cases} \tag{3.5}$$

where HR is the set of household respondents and HNR is the set of household nonrespondents. As not all household nonrespondents would qualify for the survey, $p2_{eli}$ is the proportion of respondents that make it through the screener who are eligible. Household respondents are cases where a screener is completed after the household status is confirmed. Household nonrespondents are cases where household status was confirmed, but no screener was completed. $\delta_i(c)$ defines the household nonresponse adjustment groups. $\delta_i(c) = 1$ if the household is in cell c and $\delta_i(c) = 0$ otherwise.

Non-response adjustment groups were defined within sample frame (i.e., ABS and Prepaid cell). Two sets of variables were considered for defining the nonresponse adjustment groups. The first set of variables included variables similar to those used in the past cycles of CHIS. These variables included urban status, detailed phone append status (landline phone number appended, cell phone number appended and no phone appended) and language of mailing materials (Hispanic dominant, Asian dominant and English). The second set of variables included variables from the Census Planning Database at the block group level. These were low response score, percent Hispanic, percent non-Hispanic white, percent language other than English spoken at home, percent college educated, percent poor, and percent with no health insurance.

A classification and regression tree (CART) analysis was run to identify which of these variables would make good nonresponse adjustment cell definitions. The variables that were most significant in the CART analysis were used to define the household non-response groups for the respective samples. For the main address-based sample and LBC oversample, detailed phone append status was significant in the model and was used to define the household nonresponse adjustment cells. For the prepaid sample, no variables were significant in the model so the nonresponse adjustment was done overall.

3.4 Calibration to Low Response Score from the Census Planning Database

At this point the household weights for the main address-based sample were calibrated to match the low response score (LRS) from the Census Planning Database. A five-category variable was created for the ABS sample that divided the targeted census block groups into quintiles based on the LRS. Then the household weights for the main ABS were calibrated to match the occupied household distribution from the Census Planning Database.

This weight, $HHA3W_i$, is computed as:

$$HHA3W_i = HHA3F_{gi} \times HHA2W_i \tag{3.6}$$

where $HHA3F_{gi}$ is the low response score calibration adjustment is computed as:

$$HHA3F_{gi} = \begin{cases} N_g / \sum_{i \in g} HHA2W_i\,,\ i \in \ main\ ABS\ sample \\ 1,\ i \in PPD\ cell\ and\ LBC\ ABS\ oversamples \end{cases} \tag{3.7}$$

where g denotes the low response score quintile and N_g is the number of occupied housing units in quintile g.

3.5 One-Year Household Weight

The final one-year household weight is a product of the base weight and the three adjustment factors:

$$HHW_i = BW_i \times HHA1F_i \times HHA2F_i \times HHA3F_i = HHA3W_i \tag{3.8}$$

4. ADULT WEIGHTING

A final weight was created for each adult extended interview. Below, we detail the approach used to calculate an analysis weight for adults. Specifically, we define the initial base weights for the randomly selected adult within the household in Section 4.1. Nonresponse to the adult interview request is addressed next (Section 4.2), followed by composite adjustments for overlapping sample frames (Section 4.3), then pre-calibration trimming (Section 4.4). The weights for the entire sample are then calibrated to estimated population projections (Section 4.5). The final adult analysis weight is summarized in Section 4.6. Statistics for the adjustments and the final adult weights are provided in Appendix B.

4.1 Number of Adults Adjustment

The first adjustment in the adult weighting adjusts for the number of eligible adults in the household. One eligible adult was selected with equal probability from all those residing in the household. Thus, the number of adults adjustment is equal to the number of eligible adults in the sampled household. For the prepaid cell sample, this adjustment was 1.0 if the screener respondent is eligible for the oversample and 0 if they are ineligible.

As a result, the number of adults base weight, $ADA0W_i$, is defined as the product of the total household weight, HHW_i, and the number of adults adjustment factor, AD_i:

$$ADA0W_i = AD_i \times HHW_i \tag{4.1}$$

where AD_i is the number of eligible adults in the household for respondent i. Consistent with past renditions of CHIS, values greater than three were truncated to an upper bound of three to limit the variation in the weights.

4.2 Adult Nonresponse Adjustment

Some households completed the screener interview, but the sampled adult did not complete the extended adult interview. To account for sampled adults who did not complete the extended interview, we include an adjustment for extended interview nonresponse. This was accomplished via a standard weighting class correction by specified groups.

A CART model was run to determine which variables best predicted adult response. The variables included in the model were language (English, Spanish, other language), parental status (sampled adult was a parent, or not), number of adults in the household, and adult screener respondent (sampled adult was screener respondent, or not). The only variable found to be predictive of response was adult screener respondent for the main ABS sample. The non-response adjustment cells for the main sample were defined within geographic strata. For the prepaid cell sample, parental status was found to be predictive of adult response and was used to define non-response adjustment cells. For the Long Beach city oversample, each ZIP code was treated as a non-response adjustment cell. Cells were collapsed within stratum if cell sizes were less than 25.

The adult nonresponse adjustment weight, $ADA1W_i$ is the product of the number of adults adjustment weight, $ADA0W_i$, and the adult nonresponse adjustment factor, $ADA1F_i$.

$$ADA1W_i = ADA1F_i \times ADA0W_i \tag{4.2}$$

The adjustment factor was a simple cell-based response propensity:

$$ADA1F_i = \begin{cases} \sum_{i \in R,NR} ADA0W_i \times \delta_i(c) \Big/ \sum_{i \in R} ADA0W_i \times \delta_i(c), & \text{if } i \in \text{R} \\ 0, & \text{if } i \in NR \end{cases} \tag{4.3}$$

where R denotes eligible respondents who completed the extended adult interview and NR denotes nonrespondents. $\delta_i(c) = 1$ if the adult is in cell *c* and $\delta_i(c) = 0$ otherwise.

4.3 Adult Composite Adjustments

CHIS 2023 included the following oversamples:

4.3. a. Prepaid Cell Oversample

To better target populations not adequately covered under the ABS frame, like CHIS 2021-22, CHIS 2023 utilized a Prepaid cell (PPD) oversample and targeted 450 adult respondents for this oversample. In particular, this sample was targeted to reach in-language interviews, Hispanic and African American samples, and young adults.

4.3.b. Listed PPD Oversample

CHIS 2023 also utilized a supplemental listed PPD sample to meet targets in stratum that were underperforming in completion rate. Listed prepaid cell phones were only sampled from the following 12 geographic strata:

13. Los Angeles
    a. SPA1
    b. SPA5
14. San Diego
    a. Central
15. Santa Clara
16. Sacramento
17. Contra Costa
18. Ventura
19. San Joaquin
20. Sonoma
21. Santa Cruz
22. Merced
23. Mendocino
24. San Benito

4.3.c. Long Beach City (LBC) Oversample

CHIS 2023 also oversampled 500 adult respondents from the following 11 Zip codes in the City of Long Beach:

- 90802
- 90803
- 90804
- 90805
- 90806
- 90807
- 90808
- 90810
- 90813
- 90814
- 90815

Multiple composite adjustments were required to account for overlapping samples.

4.3.1 Adult Compositing of Main Sample and Prepaid Cell Oversample

A composite adjustment was made to combine the main sample and the prepaid cell oversample. The main prepaid cell composite adjustment, $\lambda_{MAIN,PPD}$ is computed as follows:

$$\lambda_{MAIN,PPD} = \begin{cases} n_{PPD,MAIN} / \left(n_{PPD,MAIN} + n_{PPD,OS} \right), & \textit{prepaid cell users in the main sample} \\ n_{PPD,OS} / \left(n_{PPD,MAIN} + n_{PPD,OS} \right), & \textit{prepaid cell oversample} \\ 1, & \textit{other respondents} \end{cases} \tag{4.4}$$

where $n_{PPD,MAIN}$ is the number of adult interviews from the main sample who have a prepaid cell phone and are either [a] interviewed in Spanish or Asian language, [b] ages 18-24, [c] black or [d] Hispanic and $n_{PPD,OS}$ is the number of adult interviews completed from the prepaid cell oversample.

4.3.2 Adult Compositing of Main Sample and Long Beach city Oversample

A composite adjustment was made to combine the main sample and the Long Beach city oversample. The main Long Beach composite adjustment, $\lambda_{MAIN,LBC}$, is computed as follows:

$$\lambda_{MAIN,LBC} = \begin{cases} n_{LBC,MAIN} / \left(n_{LBC,MAIN} + n_{LBC,OS} \right), & \textit{Long Beach city respondents in the main sample} \\ n_{LBC,OS} / \left(n_{LBC,MAIN} + n_{LBC,OS} \right), & \textit{Long Beach city oversample respondents} \\ 1, & \textit{other respondents} \end{cases} \tag{4.5}$$

where $n_{LBC,MAIN}$ is the number of interviews from the main sample completed with adults in Long Beach city and $n_{LBC,OS}$ is the number of interviews completed from the Long Beach city oversample.

4.3.3 Adult Compositing of Main Sample and Listed Prepaid Cell Oversample

A composite adjustment was made to combine the main sample and the listed prepaid cell oversample. The main listed prepaid cell composite adjustment, $\lambda_{MAIN,LPPD}$ is computed as follows:

$$\lambda_{MAIN,LPPD} = \begin{cases} n_{LPPD,MAIN} / \left(n_{LPPD,MAIN} + n_{LPPD,OS} \right), & \textit{listed prepaid cell users in the main sample} \\ n_{LPPD,OS} / \left(n_{LPPD,MAIN} + n_{LPPD,OS} \right), & \textit{listed prepaid cell oversample} \\ 1, & \textit{other respondents} \end{cases} \tag{4.6}$$

where $n_{LPPD,MAIN}$ is the number of interviews from the main sample who have a listed prepaid cell phone and are in the prepaid cell target geography and $n_{LPPD,OS}$ is the number of adult interviews completed from the listed prepaid cell oversample.

4.3.4 Adult Compositing of Long Beach city Oversample and Prepaid Cell Oversample

A composite adjustment was made to combine the Long Beach city oversample and the prepaid cell oversample. The Long Beach prepaid cell composite adjustment, $\lambda_{LBC,PPD}$, is computed as follows:

$$\lambda_{LBC,PPD} = \begin{cases} n_{PPD,LBC}/\left(n_{PPD,LBC} + n_{LBC,PPD}\right), & \textit{Long Beach city oversample respondents who have a prepaid cell phone} \\ n_{LBC,PPD}/\left(n_{PPD,LBC} + n_{LBC,PPD}\right), & \textit{Prepaid cell oversample respondents who live in Long Beach city} \\ 1, & \textit{other respondents} \end{cases}$$

(4.7)

where $n_{PPD,LBC}$ is the number of interviews from the Long Beach city oversample completed with adults who have a prepaid cell phone and $n_{LBC,PPD}$ is the number of adult interviews completed from the prepaid cell oversample who live in Long Beach city.

4.3.5 Adult Compositing of Regular Prepaid Oversample and Listed Prepaid Cell Oversample

A composite adjustment was made to combine the regular prepaid cell oversample and the listed prepaid oversample. This prepaid composite adjustment, $\lambda_{PPD,LPPD}$, was computed as follows:

$$\lambda_{PPD,LPPD} = \begin{cases} n_{LPPD,PPD}/\left(n_{LPPD,PPD} + n_{LPPD,OS}\right), & \textit{Prepaid cell respondents with a listed prepaid phone in the target area} \\ n_{LPPD,OS}/\left(n_{LPPD,PPD} + n_{LPPD,OS}\right), & \textit{Listed prepaid cell oversample respondents} \\ 1, & \textit{other respondents} \end{cases}$$

where $n_{LPPD,PPD}$ is the number of prepaid cell interviews completed with adults in the target area who have a listed prepaid phone and $n_{LPPD,OS}$ is the number of interviews conducted from the listed prepaid cell oversample.

4.3.6 Final Adult Compositing

The adult composite adjustment weight, $ADA2W_i$ is the product of the adult nonresponse adjustment weight, $ADA1W_i$, and the adult composite adjustment factor, $ADA2F_i$.

$$ADA2W_i = ADA2F_i \times ADA1W_i \tag{4.8}$$

The adjustment factor is the product of the five adjustments described above.

$$ADA2F_i = \lambda_{MAIN,PPD} \times \lambda_{MAIN,LBC} \times \lambda_{MAIN,LPPD} \times \lambda_{LBC,PPD} \times \lambda_{PPD,LPPD} \tag{4.9}$$

4.4 Pre-Calibration Trimming

The adult weight to this point is a product of the base weight from section 3 and the adjustments noted in Sections 4.1, 4.2, and 4.3. This resulting weight was trimmed at the 2^{nd} and 98^{th} percentiles within strata. A total of 786 weights were trimmed across the 21,671 cases.

4.5 Calibration Adjustment to Department of Finance Projections

We calibrated the trimmed base weights to adjusted values of population projections supplied by the State of California's Department of Finance. Population estimates associated with California residents living in group quarters (e.g., nursing homes, prisons) and others who were not eligible for CHIS was estimated and excluded from the population controls, using techniques documented in Chapter 7 of this report. The calibrated weight was calculated as:

$$ADA3W_i = ADA2W_i \times AA1_i \qquad (4.10)$$

where $AA1_i$ is the calibration adjustment from the WTADJUST procedure.

Calibration variables, calculation of the estimated calibration control totals, and information associated with the calibration procedure are detailed in Chapter 7. The model covariates and interactions mirrored those used in prior rounds of CHIS (see Section 7.2).

4.6 Adult One-Year Analysis Weight

The resulting adult weights, $ADA3W_i$, is the final one-year adult weight. There was no trimming done after the WTADJUST procedure was run.

5. CHILD WEIGHTING

Children, ages 11 years and younger, of the randomly chosen adult in households participating in CHIS were also eligible for the study. Information on the children and interview responses were collected from the adult participant.

Below, we describe how the child (proxy interview) analysis weights were calculated. The weighting steps follow those discussed for the adult weights. Specifically, we define the base weight for the child weights in Section 5.1 that were then adjusted to account for nonresponse in Section 5.2, and to account for overlapping sample frames in Section 5.3. These weights were then trimmed (Section 5.4) and calibrated to population projections (Section 5.5). The child one-year analysis weight is shown in Section 5.6. Statistics for the adjustments and the final child weights are provided in Appendix B.

5.1 Base Weights

The child base weights are necessary to account for the disproportionate sampling of children by age group within household. Specifically, children ages 0-5 were given twice the likelihood of selection than children 6-11 by study design. If $n1$ is the number of children age 0-5 of the sampled adult in the household and $n2$ is the number of children 6-11 of the sampled adult in the household, then probability that a child is sampled, $CHA0_i$, is defined as:

$$CHA0_i = \begin{cases} 2/[(2 \times n1) + n2], & 0-5 \ sampled \\ 1/[(2 \times n1) + n2], & 6-11 \ sampled \end{cases} \tag{5.1}$$

The child base weight also needs to account for the different probability of child selection across households based on the number of adults and parents in the households. Households with two parents have twice the probability of selecting a parent than households with only one parent (and other adults in the household). If we let P_i be the number of parents in household i, and AD_i the number of the adults in the household (capped at 3), then the resulting child-level base weight is defined as:

$$CHW0_i = \begin{cases} HHW_i/[CHA0_i \times (P_i/AD_i)], & i \in ABS \ sample \\ HHW_i/CHA0_i, & i \in prepaid \ cell \ sample \end{cases} \tag{5.2}$$

where HHW_i is the household weight defined in Section 3.5.

5.2 Child Nonresponse Adjustment

We calculate a child nonresponse adjustment in the same manner as the adult nonresponse adjustment described in Section 4.2. This weighting adjustment accounts for households that have an eligible child, but no child interview is completed, either because of adult nonresponse or child nonresponse. The adjustment cells are defined by sex within sampling stratum. Small cells were collapsed within stratum to increase the number of respondents in each cell.

$$CHA1W_i = CHA1F_i \times CHW0_i \tag{5.3}$$

The adjustment factor, $CHA1F_i$, is:

$$CHA1F_i = \begin{cases} \dfrac{\sum_{i \in CHR,CHNR} CHW0_i \times \delta_i(c)}{\sum_{i \in CHR} CHW0_i \times \delta_i(c)}, & \text{if } i \in CHR \\ 0, & \text{if } i \in CHNR \end{cases} \tag{5.4}$$

where CHR are child-interview respondents and CHNR are child interview non-respondents. We define c as the child nonresponse adjustment cell defined using sex of child and geographic stratum. $\delta_i(c) = 1$ if the case is in the adjustment cell and $\delta_i(c) = 0$ otherwise.

5.3 Child Composite Adjustments

The same composite adjustments made for the adult weights were also made for the child weights.

$$CHA2W_i = CHA2F_i \times CHA1W_i \tag{5.5}$$

The adjustment factor, $CHA2F_i$, is the product of the two adjustments described in Section 4.3.

$$CHA2F_i = \lambda_{MAIN,PPD} \times \lambda_{MAIN,LBC} \times \lambda_{MAIN,LPPD} \times \lambda_{LBC,PPD} \times \lambda_{PPD,LPPD} \tag{5.6}$$

5.4 Pre-Calibration Trimming

The child weight to this point is a product of the base weight from Chapter 3 and the adjustments noted from Sections 5.1, 5.2, and 5.3. The child weights were trimmed at the 2nd and 98th percentiles within region. A total of 126 cases had child weights trimmed.

5.5 Calibration Adjustment to Department of Finance Projections

The child data was calibrated to target population parameters like the adult data. The calibrated weight was calculated as:

$$CHA3W_i = CHA2W_i \times AA2_i \tag{5.7}$$

where $AA2_i$ is the calibration adjustment from the WTADJUST procedure.

Calibration variables, calculation of the estimated calibration control totals, and information associated with the calibration procedure are detailed in Chapter 7. The model covariates and interactions mirrored those used in prior rounds of CHIS (see Section 7.2).

5.6 Child One-Year Analysis Weight

The resulting child weight, $CHA3W_i$, is the final one-year child weight. There was no trimming done after the WTADJUST procedure was run.

6. ADOLESCENT WEIGHTING

Adolescent children, ages 12 to 17, of the randomly chosen adult were eligible for the study. In contrast to the child (proxy) interview, one randomly chosen adolescent was recruited to conduct an interview only after receiving permission from a parent.

Below, we describe our approach to calculating an adolescent analysis weight for analyzing an annual CHIS data file. Steps to calculate the adolescent weight follow those specified for the child weight. Specifically, we define the adolescent base weight in Section 6.1 that were then adjusted to account for nonresponse in Section 6.2, and to account for overlapping sample frames in Section 6.3. These weights were then trimmed (Section 6.4) and calibrated to population projections (Section 6.5). Statistics for the adjustments and the final adolescent weights are provided in Appendix B.

6.1 Base Weights

As in the child weighting, the initial weights for the adolescents incorporate the probability of sampling the adult and the probability of sampling an adolescent among all adolescents associated with the sampled adult. The initial weight, $TNW0_i$, is computed as

$$TNW0_i = \begin{cases} HHW_i \times TCNT_i/(P_i/AD_i)\,, & i \in ABS\ sample \\ HHW_i \times TCNT_i, & i \in prepaid\ cell\ sample \end{cases} \tag{6.1}$$

where P_i is the number of parents in household i, AD_i is the number of adults in the household (capped at 3), and $TCNT_i$ is the number of eligible adolescents of the sampled parent. HHW_i is the household weight defined in Section 3.5.

6.2 Adjustment for Adolescent Nonresponse

An adolescent nonresponse adjustment is made in the same manner as the adult and child nonresponse adjustments described in Sections 4.2 and 5.2. This weighting adjustment accounts for households that have an eligible adolescent, but no adolescent interview was completed.

$$TNA1W_i = TNA1F_i \times TNW0_i \tag{6.2}$$

The adjustment factor, $TNA1F_i$, is:

$$TNA1F_i = \begin{cases} \sum_{i \in TNR,TNNR} TNW0_i \times \delta_i(c) \Big/ \sum_{i \in TNR} TNW0_i \times \delta_i(c), & \text{if } i \in TNR \\ 0, & \text{if } i \in TNNR \end{cases} \tag{6.3}$$

where TNR are adolescent interview respondents and TNNR are adolescent interview non-respondents. We define c as the adolescent nonresponse adjustment cell defined using stratum. $\delta_i(c) = 1$ if the case is in the adjustment cell and $\delta_i(c) = 0$ otherwise. The adjustment cells are defined by sampling stratum.

6.3 Adolescent Composite Adjustments

The same composite adjustments made for the adult and child weights were also made for the adolescent weights.

$$TNA2W_i = TNA2F_i \times TNA1W_i \tag{6.4}$$

The adjustment factor, $TNA2F_i$, is the product of the two adjustments described in Section 4.3.

$$TNA2F_i = \lambda_{MAIN,PPD} \times \lambda_{MAIN,LBC} \times \lambda_{MAIN,LPPD} \times \lambda_{LBC,PPD} \times \lambda_{PPD,LPPD} \tag{6.5}$$

6.4 Pre-calibration Trimming

The adolescent weight to this point is a product of the base weight from Chapter 3 and the adjustments noted from Section 6.1, 6.2, and 6.3. Weights were trimmed at the 5th and 95th percentiles within region. A total of 90 cases had adolescent weights trimmed.

6.5 Calibration Adjustment to Department of Finance Projections

The adolescent data was calibrated to target population parameters like the adult data. The calibrated weight was calculated as:

$$TNA3W_i = TNA2W_i \times AA3_i \tag{6.6}$$

where $AA3_i$ is the calibration adjustment from the WTADJUST procedure.

Calibration variables, calculation of the estimated calibration control totals, and information associated with the calibration procedure are detailed in Chapter 7. The model covariates and interactions mirrored those used in prior rounds of CHIS (see Section 7.2).

6.6 Adolescent One-Year Analysis Weight

The resulting weight, $TNA3W_i$, is the final one-year adolescent weight. There was no trimming done after the WTADJUST procedure was run.

7. CALIBRATION CONTROL TOTALS

Calibration to population values is an important attribute of the CHIS weights. Section 7.1 contains an overview of weight calibration and highlights the many benefits of such efforts. Section 7.2 contains the dimensions used in the final calibration models, along with steps to address small sample size for certain dimensions. Population sources accessed for key information are detailed in Section 7.3. Steps to convert the population information into usable calibration control totals are discussed in Section 7.4.

7.1 Calibration Procedure

Calibration is a weight adjustment method where survey-estimated population counts are constrained to equal their corresponding population control totals. If the population characteristics are associated with a survey characteristic, then the estimated characteristic will have a smaller standard error with calibration compared to its size with unadjusted analysis weights (Kott, 2006; Valliant et al., 2013). Poststratification and raking are types of weight calibration. With poststratification, characteristics are interacted (e.g., sex crossed with levels of race/ethnicity) to form a relatively large number of weighting cells (classes). Using too many characteristics could result in cells with a small amount of sample, resulting in an increase in the variability of the weights and consequently a reduction in precision for estimates using these weights. Small cells are generally collapsed with larger cells to improve precision but sometimes the ad hoc collapsing can increase bias in the estimates (Kim et al., 2007). Raking (Kalton & Flores-Cervantes, 2003), in its traditional form, only using the marginal control totals and no interactions, thereby including more covariates than poststratification but excluding finer adjustments that could benefit the survey estimates.

Calibration using the WTADJUST procedure in SUDAAN (Section 2.2.2) combines the benefits of poststratification and raking by allowing many controls with constraints on the adjustment to control decrease in precision. Specifically, calibration allows a combination of marginal control (e.g., design strata) and interactions (e.g., region by sex by race/ethnicity).

Calibration adjustments were implemented to align the weight sums to person-level estimates by several characteristics. Information for the adult, child and adolescent adjustments are discussed in Sections 4.5, 5.5, and 6.5, respectively. The control totals used in the calibration models are detailed in the next section (Section 7.2). Because population totals required for the adjustment did not exist, needed population estimates were generated from population information that was available. The control total sources for the two calibration adjustments are listed in Section 7.3. Estimation methods for the CHIS control totals are detailed in Section 7.4.

In 2019, we ran 11 different calibrations to align weight sums to population estimates. We ran an untrimmed calibration along with calibrations that trimmed the weight at 1%, 2%, …,10%. We computed mean squared errors on a series of variables to decide on a final trimming.[3] There was no one trimming that resulted in a minimum mean squared error across all of the variables and differences among the trimmings were subtle. We used the 1% trim as it minimized the MSE for the majority of the variables used in the analysis. We utilized the same 1% trim for the 2023 calibration.

7.2 Calibration Model Dimensions

The 13 weight calibration dimensions used in CHIS 2023 are shown in Table 7-1. These dimensions follow those specified in prior years of the study to maximize continuity. Specifically, Dimensions 1-8 and 11 involve combinations of demographic characteristics (age, sex, race/ethnicity) and reported geography (county, region, state). Regions of the state are shown in Table 7-2. Note that the number of groups is provided in parentheses, such as primary age 1 (3) = under 12 years, 12 to 17 years, and 18 years or older shown for Dimension 1. Dimension 9 includes education of the responding adult crossed with region and Dimension 10 includes number of adults in the household crossed by primary age crossed by region. Dimension 12 interacts household tenure by region. Dimension 13 was included this year because of the oversample of Long Beach city.

Levels within the dimensions were collapsed for situations where there were fewer than 50 respondents in a cell. Table 7.1 shows the 13 calibration dimensions along with the total number of categories for each. The last column of the table shows the number of categories that were used in the calibration after collapsing. Table 7.2 shows the definition of all the variables that were used to create the 13 dimensions.

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[3] The variables used in the trimming analysis were DISTRESS, AB1, ASTCUR (adult), AB22, AH16, AH22, AI8, CA6, ASTCUR (child), TB1, and ASTCUR (adolescent).

Table 7-1. Dimensions used in weight calibration

Dimension	Variables (categories)	Total categories[1]	Categories after collapsing
1	Region (7) by primary age 1 (3) by sex (2)	42	38
2	Region (7) by secondary age (9)	63	63
3	Detailed age (13) by sex (2)	26	26
4	Geography (14) by primary age 1 (3) plus remainder (1)	43	28
5	Primary age 2 (2) by race/ethnicity (7) by region (7)	98	55
6	Primary age 1 (3) by race/ethnicity (7) by sex (2)	42	28
7	Asian groups (8) by primary age 1 (3)	24	16
8	Stratum (44) by race (3) by primary age 2 (2)	264	127
9	Region (7) by education (6)	42	35
10	Region (7) by primary age 1 (3) adults in household (3)	63	48
11	Stratum (44) by primary age 1 (3)	132	79
12	Household tenure (2) by region (7)	14	14
13	Long Beach city (3)	3	3

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] The total number of categories for each dimension is simply the product of the individual variables used to create the dimension, plus any remainder categories (dimension 4).

Table 7-2 details the variables used the 13 calibration dimensions. The number of categories is listed in parenthesis followed by a list of the dimensions that use the variable.

Table 7-2. Detailed variable definitions used in calibration dimensions

Variable	Dimensions	Categories	
Region (7)	1,2,5,9,10,12	*Northern & Sierra Counties*: Butte, Shasta, Humboldt, Lake, Mendocino, Yuba, Nevada, Sutter, Colusa, Glenn, Tehama, Del Norte, Lassen, Modoc, Plumas, Sierra, Siskiyou, Trinity, Alpine, Amador, Calaveras, Inyo, Mariposa, Mono, Tuolumne counties	
		Greater Bay Area: Santa Clara, Alameda, Contra Costa, San Francisco, San Mateo, Sonoma, Solano, Marin, Napa counties	
		Sacramento Area: Sacramento, Placer, Yolo, El Dorado counties	
		San Joaquin Valley: Fresno, Kern, San Joaquin, Stanislaus, Tulare, Merced, Kings, Madera counties	
		Central Coast: Ventura, Santa Barbara, Santa Cruz, San Luis Obispo, Monterey, San Benito counties	
		Los Angeles: Los Angeles County	
		Other Southern California: San Diego, Orange, San Bernardino, Riverside, Imperial counties	
Primary age 1 (3)	1,4,6,7,10,11	0-17 years	
		18-64 years	
		65+ years	
Sex (2)	1,3,6	Male	
		Female	
Secondary age (9)	2	0-5 years	30-39 years
		6-11 years	40-49 years
		12-17 years	50-64 years
		18-24 years	65+ years
		25-29 years	
Detailed age (13)	3	0-3 years	31-37 years
		4-7 years	38-45 years
		8-11 years	46-53 years
		12-14 years	54-64 years
		15-17 years	65-77 years
		18-24 years	78+ years
		25-30 years	

(continued)

Table 7-2. Detailed variable definitions used in calibration dimensions (continued)

Variable	Dimensions	Categories	
Geography (14)	4	Los Angeles County – Antelope Valley Los Angeles County – San Fernando Valley Los Angeles County – San Gabriel Valley Los Angeles County – Metro Los Angeles County – West Los Angeles County – South Los Angeles County – East Los Angeles County – South Bay San Diego County – North Coastal San Diego County – North Central San Diego County – Central San Diego County – South San Diego County – East San Diego County – North Inland	
Primary age 2 (2)	5,8	0-17 years 18+ years	
Race/ethnicity (7)	5,6	Latino White, not Latino Black, not Latino American Indian, not Latino Asian, not Latino Native Hawaiian, not Latino Two or more races, not Latino	
Asian groups (8)	7	Not Latino Chinese Not Latino Korean Not Latino Filipino Not Latino Vietnamese	Not Latino Japanese Not Latino South Asian Not Latino other Asian Latino or not Asian
Stratum (44)	8,11	Refer to Table 1-1 for strata definitions	
Race (3)	8	Latino Not Latino, White Not Latino, other race	
Education (6)	9	Under 18 and parent less than HS graduate Under 18 and parent HS graduate Under 18 and parent some college+ 18+, less than HS graduate 18+, HS graduate 18+, some college+	

(continued)

Table 7-2. Detailed variable definitions used in calibration dimensions (continued)

Variable	Dimensions	Categories
Number of adults in household (3)	10	One adult Two adults Three or more adults
Household tenure (2)	12	Homeowner Renter
Long Beach city (3)	13	Long Beach city Rest of Los Angeles County Rest of California

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

7.3 Sources for Population Control Totals

No individual source was available to address the calibration control total needs for CHIS. In keeping with prior rounds of the study, multiple government databases were combined to produce estimated population values used in the calibration. We describe the sources below.

7.3.1 California Department of Finance Population Predictions and Estimates

As in prior years of CHIS, the California Department of Finance (DOF) population projections was the primary source for calculating estimated control totals used in weight calibration. Population counts by county and person-level characteristics (Table 7-3) were provided for 2023 for yearly file adjustments. This sole source by year produced estimates for adult, child and adolescent weight because projections are provided by single year of age up to 100 years. Additional information on the history of the DOF projections is provided in the *CHIS 2013-2014 Methodology Series: Report 5 – Weighting and Variance Estimation*.

Table 7-3. Definition of counts available in 2023 California DOF population files

Category	Levels
County (58)	Alameda, Alpine, …, Yolo, Yuba
Age groups (101)	Age less than 1 year, Age 1 year, …, Age 100 years or more (by single year of age)
Sex (2)	Male Female
Race/ethnicity (12)	Latino White alone Latino African American alone Latino American Indian/Alaska Native alone Latino Asian alone Latino Native Hawaiian and other Pacific Islander alone Latino Two or more races Non-Latino White alone Non-Latino African American alone Non-Latino American Indian/Alaska Native alone Non-Latino Asian alone Non-Latino Native Hawaiian and other Pacific Islander alone Non-Latino Two or more races

Source: 2023 California Department of Finance projections.

The DOF projections, however, were not in perfect alignment with CHIS and additional adjustments were required. First, DOF projections followed the U.S. Office of Management and Budget (OMB) modified race definition and, as shown in Table 7-3, did not include an “other race” group (OMB, 1997). With CHIS, respondents could designate one or more of five main racial categories—White, Black/African American, American Indian/Alaska Native, Asian, or Native Hawaiian/Other Pacific Islander. All open-end responses that could not be collapsed into a single or multi-race using this groups were classified as “other” and for the purposes of weighting were imputed as one of the OMB categories. (See discussion of OMBSRREO in Section 8.4.2)

DOF projections also included California residents who live in group quarters, a population that was ineligible for CHIS. Census 2020 files were used to estimate the proportion of persons in group quarters; these values were subtracted from the DOF projections, and these proportions were removed from the DOF estimates (see Section 7.4.1).

Additionally, the person characteristics on the DOF file did not allow the estimate of population counts for all calibration dimensions. Therefore, additional sources were required for this purpose as discussed below.

7.3.2 Census 2020 Files

Data from the 2020 Census was used as source information for CHIS in three ways:

- The proportion of CHIS-ineligible residents living in group quarters was estimated from the 2020 Demographic and Housing Characteristics File (DHC). Section 7.4.1 describes the details of this process. Information available from the DHC is provided in Table 7-4.
- The DHC was also used for producing population distributions for Dimension 4 by Service Planning Areas (SPAs) within Los Angeles County and by Health and Human Services Agency (HHSA) regions within San Diego County, which were then applied to the DOF population total for that county.
- The DHC was also used for Dimension 13 to estimate the population of Long Beach city, which was applied to the DOF population total for Los Angeles County.

Table 7-4. Definition of variables available on the 2020 Demographic and Housing Characteristics File

Category	Levels
Stratum (44)[1]	
Sex (2)	Male Female
Age groups (3)	Less than 18 years old 18-64 years old 65 years old or older
Ethnicity (3)	Latino Non-Latino, White alone Other
Race (7)	White alone African American alone American Indian/Alaska Native alone Asian alone Native Hawaiian and Other Pacific Islander alone Other race alone Two or more races

Source: U.S. Census Bureau, Census 2020.

[1] Design strata (44) are defined in Table 1-1.

7.3.3 American Community Survey for California

American Community Survey (ACS) public-use one-year micro data files (PUMS) were accessed for Dimensions 7, 9, 10, and 12. These data were used to estimate the proportions of the population by Asian groups, education, household tenure, and number of adults in the household (Table 7-2). The 2022 ACS PUMS file was used for CHIS 2023 one-year weights.

7.4 Producing the Control Totals

As mentioned previously, the population control totals were estimated and not directly drawn from available sources. The procedures to calculate the estimates follow methods developed for previous rounds of the study and are detailed below. The process begins with estimating and then removing population estimates linked with those living in group quarters (Section 7.4.1) and completes with the final calculations for the 13 calibration dimensions (Section 7.4.2).

7.4.1 Removing the Population Living in Group Quarters

Population control totals were not available and instead were estimated from the source of information described previously. The procedures followed those originally developed for CHIS 2003 to maintain consistency across years. All control totals were derived from the same adjusted DOF projections to maintain consistency across dimensions. The general steps are described below.

Tabulated Population Projections. The DOF population counts were tabulated into groups defined by the cross-tabulation design stratum (44), ethnicity (Latino, Non-Latino), age group (18), race (6) and gender (2). The six levels for race in the DOF file are shown in Table 7-3 and the 18 age levels required for the calibration dimensions are shown in Table 7-5. For convenience, let T_{d6}^{DOF} represent the cross-tabulated counts for the DOF file, where year is suppressed for convenience and the race grouping (6) excluding “other”.

Estimated Group Quarters. The estimated proportion of group quarters was estimated from the 2020 Census DHC. As shown in Table 7-4, however, not all characteristics required for CHIS were available (e.g., single year of age). Consequently, assumptions were required: 1) the proportion in group quarters by single year of age within each age group (less than 18 years old, 18 to 64 years old, and 65 years old or older) was the same; and 2) the proportion in group quarters within racial group was the same across ethnicity (Latino or non-Latino).

Table 7-5. Age levels used to summarize California DOF data file

Age group	Description	Age group	Description
1	0 to 3 years old	10	30
2	4 to 5	11	31 to 37
3	6 to 7	12	38 to 39
4	8 to 11	13	40 to 45
5	12 to 14	14	46 to 49
6	15 to 17	15	50 to 53
7	18 to 24	16	54 to 64
8	25	17	65 to 77
9	26 to 29	18	78 years and older

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.
Note: DOF = Department of Finance.

Three sets of estimated control totals excluding group quarters were calculated from the 2020 Census DHC by different groups. The first total set was defined as

$$D_{1m}^{DHC.\overline{GQ}} = D_{1m}^{DHC} - D_{1m}^{DHC.GQ} \tag{7.1}$$

where D_{1m}^{DHC} was the total population of California within group m, $D_{1m}^{DHC.GQ}$ was the corresponding population living in group quarters, and m was defined as cells created by crossing strata (44), race (7), age group (3) and sex (2). The levels of these variables are shown in Table 7-4.

The second set of control totals were defined as

$$D_{2p}^{DHC.\overline{GQ}} = D_{2p}^{DHC} - D_{2p}^{DHC.GQ} \tag{7.2}$$

where $D_{2\mathrm{p}}^{DHC}$ was the total population of California within group p, $D_{2\mathrm{p}}^{DHC.GQ}$ was the corresponding population living in group quarters, and p was defined as cells created by crossing strata (44), ethnicity (3), age group (3) and sex (2).

The third set of controls were calculated as

$$D_{3q}^{DHC.\overline{GQ}} = D_{3q}^{DHC} - D_{3q}^{DHC.GQ} \tag{7.3}$$

where D_{3q}^{DHC} was the total population in California within group q, $D_{3q}^{DHC.GQ}$ was the corresponding population living in group quarters, and q was defined as cells created by the cross of strata (44) and age group (less than 18 years old, 18 years and older).

Using the similarity assumptions above and the three sets of control totals – $D_{1m}^{DHC.\overline{GQ}}$ in (7.1), $D_{2p}^{DHC.\overline{GQ}}$ in (7.2) and $D_{3q}^{DHC.\overline{GQ}}$ in (7.3) – that all excluded group quarters, 2020 Census DHC counts with group quarters removed were estimated as

$$T_{d7}^{DHC.\overline{GQ}} = T_{mp}^{DHC} \times a_{mp} \tag{7.4}$$

where T_{mp}^{DHC} were the 2020 Census DHC population counts within cross-classified groups defined in Table 7-5, a_{mp} was the adjustment applied based on raking the counts to the control totals, and *d7* identifies the groups defined by the cross-classification of design stratum (44), ethnicity (Latino, Non-Latino), age group (18), race (7) including "other" and gender (2). The corresponding methodology was applied with the total population counts including group quarters to derive T_{d7}^{DHC}. Thus, the proportion of group quarters in cell *d* was calculated as

$$p_{d7}^{DHC.\overline{GQ}} = {T_{d7}^{DHC.\overline{GQ}}} \Big/ {T_{d7}^{DHC}} \tag{7.5}$$

This proportion was then applied to the yearly DOF files where ratios associated with the "other" category were assumed to be equivalent to a combination of information from the other racial groups (see, for example, *CHIS 2013-2014 Methodology Series: Report 5 – Weighting and Variance Estimation* for the justification). Thus,

$$T_{d6}^{DOF.\overline{GQ}} = p_{d7}^{DHC.\overline{GQ}} \times T_{d6}^{DOF} \tag{7.6}$$

The estimated residential population, excluding group quarters, within cells defined by stratum (44), ethnicity (Latino, Non-Latino), age group (18), race (6) and gender (2). The estimated proportion of the California residential population that live in grouped quarters was 2.4%.

7.4.2 Computing the Control Totals

Values calculated with (7.6) were tabulated across the estimation cells to form the non-group quarters control totals for calibration dimensions 1-3, 5, 6, 8 and 11. Census tract information was used to align the 2020 Census DHC file to SPA and San Diego HSSA region to form subarea-specific proportions. These were applied to the Los Angeles and San Diego adjusted counts for tabulating control totals for Dimension 4. The DHC file was also used to create control totals for dimension 13 (Long Beach city). For Dimension 7, the proportion by ethnicity group (Latino, non-Latino) for the Asian population was tabulated from 2022 ACS PUMS data and applied to the adjusted DOF counts. ACS data were also used for dimension 9 (adult's education), dimension 10 (number of adults in the household), dimension 12 (household tenure).

8. IMPUTATION PROCEDURES

Item nonresponse occurs when a sample member should have but does not provide a response to a question. This excludes items that are skipped because of responses to prior routing questions. Item nonresponse also results if a response is deemed infeasible based on quality reviews and removed. Imputation replaces the missing values with valid responses, thereby enabling complete-case analysis and analysis weight creation. Imputation procedures were used for a select set of variables for CHIS 2023.

This chapter describes the magnitude of item nonresponse by year for variables critical to producing the CHIS analysis weights, along with methods to address the missing information. Section 8.1 contains a preview of the variables subject to imputation, along with details of the methods used to supply the missing information. Identification of the methods used is communicated to the user community through a set of imputation indicator variables accompanying the data. Section 8.2 summarizes the imputation results for variables associated with the geographic location of the sampled households. Information on imputed values for household characteristics relevant to all interviews within the household (adult, adolescent, and child) is given in Section 8.3. Section 8.4 concludes this chapter with a discussion of the person-level variables important not only for the weights but also subgroup estimation with the CHIS data.

8.1 Imputed Variables and Methods

Table 8-1 lists by type the variables critical to the creation of CHIS analysis weights that were examined for imputation. The questionnaire response variables used to generate the initial values are provided. The response variables are listed in priority order, where priority was based on response source. For example, we assigned self-reported age (SRAGE) for adults the value from adult interview (AAGE); if this information was missing, then information was obtained from the corresponding screener variable (SC62_AGE, SCE2_AGE).

Table 8-1. Description of imputed variables by year

Variable Type	Variable Name	Variable Description	Response Variables
Geographic	SR_COUNTY_FIPS	County	For the ABS sample, the geographic variables were solely based on sample information. For the prepaid sample, AO2, AM8, AM9, SAH42
	SRZIP	ZIP Code	
	SRSTRATA	Stratum	
	SR_LASPA	Los Angeles Service Planning Area (SPA)	
	SR_HR	San Diego Health Service Region (HSR)	
Household	SRTENR	Household tenure	AK25, Own/Rent Sample Appended Flag
	ELIG_KID_0_5	Number of interview-eligible kids ages 0-5	SC13A2_01 –SC13A2_20, SC15A_1 – SC15A_20, SC14A1, SC14A_01-SC14A_20, SC14C_01 –SC14C_20, ADULT_INDEX, TEEN_INDEX, CHILD_INDEX
	ELIG_KID_6_11	Number of interview-eligible kids ages 6-11	SC13A2_01 –SC13A2_20, SC15A_1 – SC15A_20, SC14A1, SC14A_01-SC14A_20, SC14C1, SC14C_01-SC14C_20, ADULT_INDEX, TEEN_INDEX, CHILD_INDEX
	ELIG_TEEN	Number of interview-eligible adolescents	SC13A2_01 –SC13A2_20, SC15A_1 – SC15A_20, SC14A1, SC14A_01-SC14A_20, SC14C1, SC14C_01-SC14C_20, ADULT_INDEX, TEEN_INDEX, CHILD_INDEX
	PARENT_CHILD_HH	Number of parents for the selected child	SC14A_01-SC14A_20, SC14C1, SC14C_01-SC14C_20, PERSNUM_CHILD
	PARENT_TEEN_HH	Number of parents for the selected adolescent	SC14A_01-SC14A_20, SC14C1 SC14C_01-SC14C_20, PERSNUM_TEEN

(continued)

Table 8-1. Description of imputed variables by year (continued)

Variable Type	Variable Name	Variable Description	Response Variables
Person	SRAGE	Age	AAGE, CAGE, TAGE, SC62, SC6E2
	SRSEX	Sex	AD66C, AD65E,CA73, CA1B, TA21B, TA20B
	SREDUC	Educational Attainment	AH47
	SRH	Self-Reported Latino	AA4, CH1, TI1
	SRW	Self-Reported White	AA5A_A - AA5A_G, CH3_A - CH3_G, TI2_a – TI2_G
	SRAA	Self-Reported African American	AA5A_A - AA5A_G, CH3_A - CH3_G, TI2_a – TI2_G
	SRAS	Self-Reported Asian	AA5A_A - AA5A_G, CH3_A - CH3_G, TI2_a – TI2_G
	SRAI	Self-Reported American Indian/Alaska Native	AA5A_A - AA5A_G, CH3_A - CH3_G, TI2_a – TI2_G
	SRPI	Self-Reported Native Hawaiian and Other Pacific Islander	AA5A_A - AA5A_G, CH3_A - CH3_G, TI2_a – TI2_G
	SRO	Self-Reported Other	AA5A_A - AA5A_G, CH3_A - CH3_G, TI2_a – TI2_G
	SRCH	Self-Reported Chinese	AA5E_A – AA5E_G, CH7_A – CH7_G, TI2D_A – TI2D_G
	SRPH	Self-Reported Filipino	AA5E_A – AA5E_G, CH7_A – CH7_G, TI2D_A – TI2D_G
	SRKR	Self-Reported Korean	AA5E_A – AA5E_G, CH7_A – CH7_G, TI2D_A – TI2D_G
	SRJP	Self-Reported Japanese	AA5E_A – AA5E_G, CH7_A – CH7_G, TI2D_A – TI2D_G
	SRVT	Self-Reported Vietnamese	AA5E_A – AA5E_G, CH7_A – CH7_G, TI2D_A – TI2D_G
	SRASO	Self-Reported Other Asian	AA5E_A – AA5E_G, CH7_A – CH7_G, TI2D_A – TI2D_G
	OMBSRREO	OMB Race/ Ethnicity Group	SRH, SRO, SRW2, SRAA2, SRAS2, SRAI2, SRPI2
	OMBSRASO	OMB non-Latino Asian Group	SRH, SRAS, SRCH, SRPH, SRKR, SRJP, SRVT, SRASO

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

The type and item nonresponse rate of each variable dictated the imputation methodology. The various methods used for CHIS are shown in Table 8-2, along with the codes for the imputation indicator (flag) created for each weighting variable.

Table 8-2. Description of imputation indicators

Imputation Flag	Definition
0	Reported data; no imputation
1	Missing data; deterministic (i.e., logical) imputation[1]
2	Inconsistent data removed; deterministic (i.e., logical) imputation[1]
3	Missing data; random assignment[2]
4	Inconsistent data; random assignment[2]
5	Missing data; hot-deck imputation[3]
6	Inconsistent data; hot-deck imputation[3]
7	Missing data; external data source assignment
8	Inconsistent data; external data source assignment

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.
[1] Values assigned based on other information in the interview
[2] Values randomly assigned from distribution of all possible values
[3] Values randomly obtained from donor record with reported data

A brief description of the imputation methods is as follows.

- *Deterministic imputation* uses responses to other variables within the respondent interview to assign a value. An example of deterministic imputation is imputing a female gender when the respondent has indicated a past pregnancy.
- *Random assignment* consists of randomly populating a value in place of the missing information based on the distribution of responses for that variable. One example of a random assignment is imputing a missing age based on the distribution of respondent ages in a stratum. Only variables with very few missing responses were imputed using deterministic or random assignment. While the item nonresponse may be related to other variables in the dataset, we assumed that any bias introduced through deterministic or random assignment would be negligible.
- *Hot-deck imputation* was used when the concerns about estimated bias from item nonresponse outweighed the applicability of the two imputation methods previously discussed. In hot-deck imputation, records with missing values are given values from

randomly selected donors that were in the same imputation class as the recipient (RTI 2012; Andridge and Little, 2010; Brick and Kalton, 1996). Imputation classes are ideally formed through the cross-classification of covariates (variables) associated with the weighting variables in the group and with patterns of item nonresponse. We used results from classification and regression tree (CART) models to create imputation classes (Breiman et al., 1984) with input variables shown in Table 8-3.

- *External data source assignment*: We imputed missing values using a *data source external to CHIS*, including population patterns derived from administrative data.

Table 8-3. Input variables for CART models to create imputation classes

Variable	Definition
SC5A	Number of adults in the household
CHLD_INDEX	Presence of children in the household
CREGION	California region
ELIG_KID_0_5	Number of children aged 0-5 years related to the selected adult
ELIG_KID_6_11	Number of children aged 6-11 years related to the selected adult
ELIG_TEEN	Number of adolescents aged 12-17 years related to the selected adult
POVERTY	Poverty status
SRAGE	Self-reported age
SREDUC	Self-reported educational attainment
SRH	Self-reported Latino
SRRACE	Self-reported race
SRSEX	Self-reported sex
SRSTRATA	Self-reported stratum
SRTENR	Self-reported tenure
TEEN_INDEX	Presence of adolescents in the household

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Several quality evaluations were conducted on the data before and after imputation. For example, data were subjected to an extensive cleaning process to ensure consistency of the responses within an interview (internal response consistency) and across interviews within a household (external response consistency) for the donor cases. Once completed, we examined the imputed response for internal and external consistency.

8.2 Geographic Characteristics

Records were geocoded to specific latitude and longitude coordinates based on the sampled address. This section describes the geographic responses imputed when missing to allow coordinate assignment by the geocoding process.

8.2.1 Self-reported ZIP Code

For the ABS sample in CHIS 2023, none of the geographic variables required imputation. For the prepaid cell oversample- in CHIS 2023, we imputed zip code for the missing cases using SRSTRATA and the phone area code.

Table 8-4 shows the unweighted item nonresponse for SRZIP.

Table 8-4. Item nonresponse for self-reported zip code

Variable and Source of Data	All Modes	
	n	pct[2]
SRZIP (Self-reported ZIP code)		
Sampled values	21,630	99.8
Imputed values	41	0.2
Total	21,671	100.0

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of cases within variable.

8.2.2 Self-reported Stratum and Substratum

As with SRZIP, stratum (SRSTRATA), Los Angeles Service Planning Areas (SR_LASPA) and San Diego Health Service Regions (SR_HR) were computed from the sampled address and where needed were imputed based on the imputed SRZIP for the prepaid cell cases. Table 8-5 shows the unweighted rates for these variables.

Table 8-5. Item nonresponse for stratum, Los Angeles SPA, and San Diego HSR

Variable and Source of Data	All Modes	
	n	pct[1]
SRSTRATA (Self-reported stratum)		
Sampled values	21,630	99.8
Imputed values	41	0.2
Total	21,671	100.0
SR_LASPA (Self-reported Los Angeles County Service Planning Area)		
Sampled values	21,630	99.8
Imputed values	41	0.2
Total	21,671	100.0
SR_HR (Self-reported San Diego County Health Service Region)		
Sampled values	21,630	99.8
Imputed values	41	0.2
Total	21,671	100.0

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of cases within variable.

8.2.3 Self-reported Region and Urbanicity

Two additional geographic variables were created based on the results of the geographic imputation. CREGION groups counties into seven distinct regions (Table 7-2). URBAN is a variable that classifies all records in strata 1-15 as urban (URBAN=1) and the remaining records as rural (URBAN=2). Both variables were based on SRZIP.

8.3 Household Characteristics

To calculate the household weights, the foundation for the person-level analysis weight, all participating households must have data for certain characteristics. This section outlines the imputation methodology for these household variables.

8.3.1 Household Tenure

Missing values for household tenure (SRTENR) were imputed using hot-deck imputation. CART created imputation classes using household poverty (POVERTY). Table 8-6 shows the item nonresponse distribution for this variable.

Table 8-6. Item nonresponse for self-reported household tenure

Variable and Source of Data	All Modes	
	n	pct[1]
SRTENR (Household tenure)		
Reported values	21,126	97.5
Imputed values	545	2.5
Total	21,671	100.0

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of cases within variable.

8.3.2 Household Composition

Number of Eligible Children by Age Group

The number of children related to the adult respondent was required for household and child-level weights. Because children in different age groups had different probabilities of selection, we separated the number of eligible children by age group. Missing values were imputed using hot-deck imputation with reported stratum, the type of respondents (adult, child, or adolescent) in each household and the parent’s race/ethnicity as imputation covariates. The item nonresponse for the two age-group variables is shown in Table 8-7.

Table 8-7. Item nonresponse for number of study-eligible children by age group

Variable and Source of Data	All Modes	
	n	pct[1]
ELIG_KID_0_5 (Self-reported number of eligible children ages 0-5)		
Reported values	21,506	99.2
Imputed values	165	0.8
Total	21,671	100.0
ELIG_KID_6_11 (Self-reported number of eligible children ages 6-11)		
Reported values	21,506	99.2
Imputed values	165	0.8
Total	21,671	100.0

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of cases within variable.

Number of Eligible Adolescents

The number of adolescents related to the adult respondent was required for the household and adolescent-level weights. Missing values were imputed using hot-deck imputation with reported stratum, the type of respondents (adult, child, or adolescent) in each household and the parent's race/ethnicity as imputation covariates. The item nonresponse for this variables is shown in Table 8-8.

Table 8-8. Item nonresponse for number of study-eligible adolescents

Variable and Source of Data	All Modes	
	n	pct[1]
ELIG_TEEN (Self-reported number of adolescents)		
Reported values	21,665	100.0
Imputed values	6	<0.1
Total	21,671	100.0

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of cases within variable.

Number of Parents of Selected Child or Adolescent

The number of parents in the household for the selected child and adolescent were used to construct the corresponding person-level weight. As there were no missing values in these variables, they were not imputed.

8.3.3 Poverty Status

Poverty status was used in the CART models to develop imputation classes for other variables. This variable was not used in the weighting process. As with the previous CHIS cycles, data for adult respondents who answered “unknown” to the household income questions were left unchanged. There were no other missing value requiring imputation.

8.4 Person-level Characteristics

Person-level weights are used to calculate population estimates for CHIS. However, the person-level variables contained item nonresponse among those classified as study respondents (Table 8-9). This section describes the imputation procedures used for each variable needed for weighting and their item nonresponse rates.

Table 8-9. Respondents by person type

Person Type	All Modes
	n
Adult	21,671
Child	3,377
Adolescent	968

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.
[1] Unweighted percent of respondents by person type.

8.4.1 Sex and Age

Self-reported sex (SRSEX) and self-reported age (SRAGE) were derived from a combination of screener and interview variables for each respondent. Table 8-10 shows the item nonresponse for SRSEX and SRAGE for each type of respondent. Because the nonresponse rates were low for SRSEX, missing values were imputed using random assignment from the distribution of responses within the associated reported stratum. SRAGE was imputed by hot-deck imputation using stratum and screener age group classification as imputation classes.

Table 8-10. Item nonresponse for self-reported sex and age by person type

Variable and Source of Data	All Modes	
	n	pct[1]
SRSEX (Self-reported sex)		
Adult	166	0.8
Child	8	0.2
Adolescent	7	0.7
SRAGE (Self-reported age)		
Adult	175	0.8
Child	0	0.0
Adolescent	0	0.0

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.
[1] Unweighted percent of imputed records among respondents in Table 8-10 by person type.

8.4.2 Race and Ethnicity

Single Race and Ethnicity

The seven self-reported race and ethnicity variables were created after upcoding all responses to the associated questions. Missing values for all variables were imputed by an iterative hot-deck imputation process using stratum and previously hot-decked race and ethnicity variables as the imputation class. Table 8-11 shows the response patterns by variable grouping for respondents missing at least one self-reported race or ethnicity value. Table 8-12 shows the response patterns for the self-reported race variables.

Table 8-11. Item nonresponse for any self-reported race value and ethnicity

Variable and Source of Data	All modes	
	n	pct[1]
One or more imputed race values		
Adult	940	4.3
Child	293	8.7
Adolescent	72	7.4
SRH (Self-reported Latin ethnicity)		
Adult	82	0.4
Child	14	0.4
Adolescent	2	0.2

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.
[1] Unweighted percent of imputed records among respondents in Table 8-11 by person type.

Table 8-12. Item nonresponse for single-response self-reported race by person type

Variable and Source of Data	All Modes	
	n	pct[1]
SRW (Self-reported race: White)		
Adult	903	4.2
Child	286	8.5
Adolescent	71	7.3
SRAA (Self-reported race: African American)		
Adult	903	4.2
Child	286	8.5
Adolescent	71	7.3
SRAI (Self-reported race: American Indian)		
Adult	903	4.2
Child	286	8.5
Adolescent	71	7.3
SRAS (Self-reported race: Asian)		
Adult	903	4.2
Child	286	8.5
Adolescent	71	7.3
SRPI (Self-reported race: Pacific Islander)		
Adult	903	4.2
Child	286	8.5
Adolescent	71	7.3
SRO (Self-reported race: Other)		
Adult	903	4.2
Child	286	8.5
Adolescent	71	7.3

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of imputed records among respondents in Table 8-12 by person type.

OMB Race/Ethnicity Variable

The weighting algorithm calibrated the survey weights to match the California Department of Finance (DOF) population estimates for race and ethnicity. Since the DOF race and ethnicity estimates were based on the revised Office of Management and Budget (OMB) 1997 standards for data collection, only five race categories are available: White, African American, Asian, American Indian, and Pacific Islander. The 2020 Census race estimates included an additional category called "Other Race" for respondents who did not report their races in one of the five categories. To match the OMB standards, the U.S. Census Bureau created a Modified Race Data Summary file (MRDSF) that recodes the "Other" respondents into one of the five OMB race codes. CHIS collected race data for the six Census race categories; therefore, the "Other" respondents need to be recoded into the five race categories. These race categories are coded into the variable OMBSRREO.

Table 8-13 shows the race classification for OMBSRREO including classifications for respondents who identify as Latino and respondents who identify as belonging to multiple races. These last two classifications were included to reduce the number of records that require imputation.

Table 8-13. Classification codes for OMB self-reported race/ethnicity

OMBSRREO Code	Description
1	Latino
2	Non-Latino White Only
3	Non-Latino African American Only
4	Non-Latino American Indian Alaskan Native Only
5	Non-Latino Asian Only
6	Non-Latino Pacific Islander Native Hawaiian Only
7	Non-Latino Two or More Races

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

The same coding and imputation procedure consistent with prior years of CHIS was used to classify all records into the five OMB race categories. The imputed self-reported race and ethnicity variables (SRH, SRW, SRAA, SRAS, SRAI, SRPI, and SRO) were used for the coding process.

Another indicator variable, MULTIRACE, was created to identify records that reported two or more races. All respondents who self-identified as Latino (SRH = 1) were coded as such regardless of any other race indications. Non-Latino respondents who either self-identified as one of the OMB race categories or "Other" (SRO = 1), and one of the OMB race categories were assigned to that race category. Non-Latino respondents who reported two or more races (MULTIRACE = 1) or who only reported multiple instances of “Other” were classified as having two or more races. Non-Latino respondents who only reported “Other” were required to have an imputed OMB race.

The hot-deck imputation procedure required temporary race variables (SRW2, SRAA2, SRAI2, SRAS2, and SRPI2) created from the self-reported single race variables. Non-Latino respondents who only reported “Other” had these variables set as missing. No other types of records were marked to be imputed. Hot-deck imputation proceeded on these variables. Adult, child and adolescent records used reported stratum, SRH, and previously imputed race and ethnicity variables as iterative imputation classes. Records were then classified into the OMB races based on the imputed data. Table 8-14 shows the results of the hot-deck procedure by person type and OMBSRREO value.

Table 8-14. Item nonresponse for office and management and budget self-reported race/ethnicity by person type

OMBSRREO Value, Person Type	All Modes	
	n	pct[1]
Latino		
Adult	24	0.1
Child	5	0.1
Adolescent	0	0.0
Non-Latino White Only		
Adult	76	0.4
Child	7	0.2
Adolescent	1	0.1
Non-Latino African American Only		
Adult	9	<0.1
Child	1	0.1
Adolescent	1	0.1
Non-Latino American Indian Alaskan Native Only		
Adult	1	<0.1
Child	0	0.0
Adolescent	0	0.0
Non-Latino Asian Only		
Adult	18	0.1
Child	6	0.2
Adolescent	1	0.1
Non-Latino Pacific Islander Native Hawaiian Only		
Adult	1	<0.1
Child	0	0.0
Adolescent	0	0.0
Non-Latino Two or More Races		
Adult	6	<0.1
Child	2	0.1
Adolescent	1	0.1

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of imputed records among respondents in Table 8-14 by person type.

OMB Asian Ethnicity Group

Records identified as Asian by the temporary variable SRAS2 were then further classified by Asian ethnicity in the variable OMBSRASO. The seven classes in OMBSRASO are listed in Table 8-15.

Table 8-15. Classification codes for office and management and budget self-reported non-Latino Asian ethnicity

OMBSRASO Code	Asian Ethnicity Indicator Variable	Description
-1	*N/A*	Latino or Non-Asian
1	SRCH	Chinese Only
2	SRKR	Korean Only
3	SRPH	Filipino Only
4	SRVT	Vietnamese Only
5	SRASO	Other Asian Ethnicity
6	SRJP	Japanese Only

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.
N/A = not applicable.

After imputation for SRAS2, six Asian ethnicity indicator variables were created based on their responses to the Asian ethnicity questions. Hot-deck imputation proceeded on these temporary variables. Adult, child and adolescent records used reported region, SRH, and SRAS2 as imputation classes. Table 8-16 shows the results of the hot-deck procedure on the single-race Asian ethnicity variables by person type.

Records were then coded into OMBSRASO based on their imputed Asian ethnicity variables. Table 8-17 shows the results of the hot-deck procedure by person type and OMBSRASO value.

Table 8-16. Item nonresponse for single-response self-reported non-Latino Asian ethnicity by person type

Single race, Person Type	All Modes	
	n	pct[1]
SRCH (OMB Asian ethnicity: Chinese)		
Adult	93	0.4
Child	22	0.7
Adolescent	4	0.4
SRKR (OMB Asian ethnicity: Korean)		
Adult	93	0.4
Child	22	0.7
Adolescent	4	0.4
SRPH (OMB Asian ethnicity: Filipino)		
Adult	93	0.4
Child	22	0.7
Adolescent	4	0.4
SRVT (OMB Asian ethnicity: Vietnamese)		
Adult	93	0.4
Child	22	0.7
Adolescent	4	0.4
SRASO (OMB Asian ethnicity: Asian Other)		
Adult	93	0.4
Child	22	0.7
Adolescent	4	0.4
SRJP (OMB Asian ethnicity: Japanese)		
Adult	93	0.4
Child	22	0.7
Adolescent	4	0.4

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of imputed records among respondents in Table 8-16 by person type.

Table 8-17. Item nonresponse for office and management and budget self-reported non-Latino Asian ethnicity by person type

OMBSRASO, Person Type	All Modes	
	n	pct[1]
Chinese only		
Adult	10	<0.1
Child	3	0.1
Adolescent	1	0.1
Korean only		
Adult	4	<0.1
Child	0	0.0
Adolescent	0	0.0
Filipino only		
Adult	3	<0.1
Child	1	<0.1
Adolescent	0	0.0
Japanese only		
Adult	0	0.0
Child	1	<0.1
Adolescent	0	0.0
Vietnamese only		
Adult	3	<0.1
Child	1	<0.1
Adolescent	0	0.0
Other Asian ethnicity		
Adult	83	0.4
Child	21	0.6
Adolescent	3	0.3

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of imputed records among respondents in Table 8-17 by person type.

8.4.3 Educational Attainment

Missing values for the educational attainment of the selected adult (SREDUC) were imputed using a hot-deck method (Table 8-18). A CART analysis identified the imputation covariates as POVERTY, SRH and OMBSRREO.

Table 8-18. Item nonresponse for self-reported educational attainment of the adult by person type

Variable and Source of Data	All Modes	
	n	pct[1]
SREDUC (Self-reported educational attainment)		
Reported values	21,571	99.5
Imputed values	100	0.5
Total	21,671	100.0

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

[1] Unweighted percent of cases within variable.

9. VARIANCE ESTIMATION

Weights detailed in Chapters 4–6 are used to generate point estimates from CHIS data. In this chapter, we discuss the calculation of precision for those estimates, most notably quantified through a standard error or the square root of the sampling variance. Section 9.1 summarizes the precision for a select number of analysis variables from the adult, child, and adolescent analysis files. Section 9.2 discusses two types of variance estimation methods that may be used for CHIS—linearization and replication. We detail the creation of the values needed for replication variance estimation in Section 9.3. This chapter concludes in Section 9.4 with information relevant for calculating estimates with standard commercial and open-source software that properly accounts for the CHIS sampling design.

9.1 Design Effects

Point estimates are only part of the story for any survey. Measures of precision, most notably the sampling error, quantify the confidence one has that a point estimate is a good representation of the true (but unknown) population parameter. For example, estimates with a small standard error (and consequently relatively high precision) are viewed more favorably than those with low precision because they enable tests of significance. Though point estimates appear to be substantively different, their large standard errors may result in an insignificant statistical test of those differences.

There are several statistics for quantifying precision of an estimate. They include:

- the standard error, or SE, defined as the square root of the sampling variance for an estimate that is specific to the survey design;
- the coefficient of variation, or CV, defined as the SE of the estimates divided by the point estimate;
- the relative variance, or rel-variance, defined as squared CV;
- the confidence interval calculated as the range of values from the lower bound (the point estimate minus a specified multiple of SE) to the upper bound (the point estimate plus the specified multiple of SE used for the lower bound); and
- the design effect, described below.

The design effect (DEFF) was developed by Leslie Kish (1965). DEFF typically quantifies the increase in a SE for an estimate from a complex sample design above the SE calculated for a single stage stratified design (stsrs) with sample proportionally allocated to strata as distributed in the population. A stsrs design is considered optimal for small SEs; deviations from this design are generally implemented to meet analytic objectives such as relatively equal sample across strata in CHIS.

DEFF for an estimate $\hat{\theta}$ is calculated as

$$DEFF = \frac{\text{var}_{\pi}(\hat{\theta})}{\text{var}_{stsrs}(\hat{\theta})} \tag{9.1}$$

where $\text{var}_{\pi}(\hat{\theta})$ is the variance estimate for the appropriate CHIS sample design, and $\text{var}_{stsrs}(\hat{\theta})$ is the variance for the stsrs design. Variance for the CHIS sample design, $\text{var}_{\pi}(\hat{\theta})$, accounts for the following aspects of the survey design using replication methods discussed in this chapter:

- **Design strata**. The ABS frame was divided into mutually exclusive strata for sampling. Main strata were defined by geography and substrata were defined by modeled household attributes.
- **Clustering**. Analyses involving the combination of adult with child or adolescent interviews would result in household-clustered estimates.
- **Over- and under-sampling of sample members**. Deviations from sampling proportional to the distribution in the population will result in either over- or under-sampling of subgroups in the population. Geographic strata were sampled at different rates to provide valid estimates in most counties and in groups of counties with smaller populations. Within the geographic strata, modeled strata were also sampled at different rates. The modeled strata were created to target households likely to contain specific subgroups of interest. These subgroups include: Asians, including Koreans and Vietnamese; Hispanics; African Americans, people with low educational attainment; non-US citizens; younger adults; and households with children.
- **Within-Household Subsampling**. Subsampling within CHIS households occurred for those with multiple adult residents contacted through a randomly chosen address, for households with multiple eligible children, and for households with multiple eligible adolescents.
- **Base weight and weight Adjustments**. As discussed in the previous sections of this report, base weights and differential weight adjustments were applied to account for differing selection probabilities across geographic and modeled strata and to reduce nonresponse bias and additional coverage bias not addressed through the nonresponse adjustments.

Design effects were computed using SPSS Complex Samples which provides summary statistics and standard errors for complex sample designs. In prior iterations of CHIS, design effects were computed using SUDAAN. In days past, DEFF was used to adjust estimates from software that could only calculate SEs for a stsrs design. Specialized software for analyzing survey data obtained through a complex, multistage design is widely available now. Hence, DEFF is most effectively used to compare before and after a weight adjustment is applied or across multiple rounds of a survey using the same sampling design. Thus, differences in DEFF between CHIS 2023 and prior rounds of the study cannot be easily explained as changes to the sampling design, weighting methodology, differential response, and the like will result in different precision estimates.

As in past rounds, CHIS DEFFs calculated for specific variables of interest will generally have values greater than one. This is typical for surveys with complex designs and weighting schemes, and with over- and under-sampling to achieve analytic objectives. The degree of deviations from one will differ by the type of estimate. For example, characteristics that are linearly associated with the calibration controls used in the CHIS final weighting step will have lower DEFFs than those with weaker associations (see, e.g., Valliant et al., 2013).

Because precision differs by questionnaire item, tables below summarize DEFF for a series of variables from the adult, adolescent and child questionnaires. Specifically, the average, maximum and minimum DEFFs are shown by person interview overall and by reported stratum are shown. Because the distribution of DEFFs are known to be non-symmetric, the median values are also provided. Finally, the average square root of DEFF, denoted as DEFT, is listed along with the other measures. DEFT aligns with SE (instead of variance as with DEFF) and also provides some measure of smoothing if the DEFFs from the set of questionnaire items analyzed vary widely.

Tables 9-1, 9-2, and 9-3 contain DEFFs and DEFTs for items selected from the adult, child and adolescent questionnaires, respectively. Each table contains the average, median, maximum and minimum DEFF along with the average DEFT, overall and by reported stratum. All calculations used the final person-level linear weights described in the previous chapters.

A total of 24 variables were chosen for the adult DEFF analyses (Table 9-1). The variables include health characteristics such as general health rating, diagnosis (asthma, diabetes, high blood pressure, heart failure/congestive, heart disease, blind/deaf, felt nervous), lifestyle (smoking, number of sexual partners, skipped meals, feel safe), preventive medicine (delayed medical care, usual source of healthcare, number of doctor visits), health insurance (Medicare/Medi-CAL, employer health insurance, other government health plan, prescription coverage), and socioeconomic and demographic variables (income, sexual orientation, marital status, education attainment, U.S. citizenship status). The average DEFT for CHIS 2023 was 1.78 overall and ranged from 0.51 to 1.92 across the reported strata.

A total of 16 variables were chosen for the child DEFF analyses (Table 9-2). These variables include health characteristics such as general health rating, diagnosis (asthma, child visited emergency room), lifestyle (park safety concerns, condition that prevents child from doing activities, how often child is read to), preventive medicine (usual healthcare location, doctor visits, delayed medical care/medication, access to childcare, prescribed medicine use, assessment or test of development), and socio economic and demographic variables (age, school attendance, knowledge of First 5 California). The average DEFT for CHIS 2023 was 1.69 overall and ranged from 0.39 to 1.92 across the reported strata.

A total of 17 variables were chosen for the adolescent DEFF analyses (Table 9-3). These variables include health characteristics such as general health rating, diagnosis (asthma, adolescent visited emergency room, felt nervous or depressed or emotionally stressed, had/needed psychological or emotional counseling), lifestyle (smoking, alcohol use, e-cigarette use, had THC, neighborhood safety concerns, sexually active, live with someone who is mentally ill), preventive medicine (usual healthcare location, doctor visits, delayed medical care/medication, get help for mental health). The average DEFT for CHIS 2023 was 1.27 overall and ranged from 0.30 to 1.68 across the reported strata. Note that design effect estimates are only provided for strata with 10 or more adolescent interviews.

Table 9-1. Design effect (DEFF) and square root DEFF (DEFT) statistics for estimates from the adult interviews, overall and by reported stratum

Stratum	Design effect (DEFF)				DEFT
	Average	Median	Minimum	Maximum	Average
State	3.32	3.16	0.17	6.69	1.78
1 Los Angeles	3.35	3.36	0.03	6.59	1.79
2 San Diego	2.44	2.26	0.15	8.02	1.50
3 Orange	3.73	3.50	0.11	10.51	1.86
4 Santa Clara	3.21	3.00	0.47	9.37	1.74
5 San Bernardino	3.19	3.51	0.12	6.25	1.72
6 Riverside	3.53	3.45	0.17	9.17	1.81
7 Alameda	3.69	3.26	0.32	11.00	1.86
8 Sacramento	3.36	3.19	0.27	9.72	1.78
9 Contra Costa	4.01	3.94	0.37	10.95	1.92
10 Fresno	3.24	3.33	0.42	9.12	1.75
11 San Francisco	2.37	2.49	0.14	6.54	1.50
12 Ventura	3.20	2.95	0.21	9.97	1.71
13 San Mateo	3.11	3.16	0.44	10.93	1.70
14 Kern	3.54	3.58	0.28	12.28	1.81
15 San Joaquin	3.92	3.61	0.19	10.00	1.90
16 Sonoma	2.85	2.73	0.32	9.36	1.62
17 Stanislaus	2.63	2.41	0.12	9.94	1.55
18 Santa Barbara	2.06	2.12	0.22	6.02	1.38
19 Solano	2.12	2.31	0.00	5.67	1.39
20 Tulare	2.55	2.28	0.13	7.87	1.52
21 Santa Cruz	1.39	1.33	0.17	4.68	1.13
22 Marin	1.27	1.13	0.12	3.60	1.07
23 San Luis Obispo	1.22	1.19	0.14	5.21	1.07
24 Placer	1.71	1.66	0.11	5.02	1.26
25 Merced	1.52	1.51	0.02	6.14	1.15

(continued)

Table 9-1. Design effect (DEFF) and square root DEFF (DEFT) statistics for estimates from the adult interviews, overall and by reported stratum (continued)

Stratum	Design effect (DEFF)				DEFT
	Average	Median	Minimum	Maximum	Average
26 Butte	1.05	1.04	0.04	2.77	0.99
27 Shasta	0.70	0.70	0.15	1.90	0.82
28 Yolo	1.03	0.95	0.07	2.27	0.97
29 El Dorado	0.88	0.89	0.08	2.21	0.90
30 Imperial	1.28	0.83	0.02	5.16	1.02
31 Napa	0.69	0.58	0.00	2.54	0.77
32 Kings	0.65	0.64	0.01	2.11	0.77
33 Madera	0.78	0.79	0.01	2.30	0.84
34 Monterey	2.13	1.94	0.22	7.30	1.38
35 Humboldt	0.46	0.45	0.05	1.30	0.65
36 Nevada	0.53	0.45	0.05	2.09	0.69
37 Mendocino	0.65	0.48	0.10	2.92	0.76
38 Sutter	0.55	0.56	0.04	1.58	0.71
39 Yuba	0.33	0.29	0.05	0.96	0.55
40 Lake	0.29	0.26	0.06	1.17	0.52
41 San Benito	0.27	0.29	0.03	0.59	0.51
42 Tehama, etc.	0.54	0.48	0.00	1.82	0.70
43 Del Norte, etc.	0.81	0.63	0.03	5.83	0.83
44 Tuolumne, etc.	1.11	0.94	0.19	4.64	1.01

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Table 9-2. Design effect (DEFF) and square root DEFF (DEFT) statistics for estimates from the child interviews, overall and by reported stratum

Stratum	Design effect (DEFF)				DEFT
	Average	Median	Minimum	Maximum	Average
State	2.88	2.82	0.81	4.36	1.69
1 Los Angeles	2.57	2.59	0.58	4.22	1.59
2 San Diego	1.93	2.00	0.12	4.09	1.34
3 Orange	3.23	3.29	0.76	6.82	1.77
4 Santa Clara	3.06	3.29	0.15	6.43	1.69
5 San Bernardino	2.78	2.95	0.67	5.20	1.62
6 Riverside	3.39	3.21	0.17	6.88	1.80
7 Alameda	3.96	4.03	0.05	6.87	1.92
8 Sacramento	2.70	2.37	0.06	5.41	1.59
9 Contra Costa	2.76	2.39	0.43	6.91	1.57
10 Fresno	2.64	2.59	0.79	6.01	1.60
11 San Francisco	3.74	3.60	0.50	6.13	1.89
12 Ventura	2.67	2.42	0.18	5.60	1.56
13 San Mateo	1.57	1.42	0.06	5.48	1.19
14 Kern	2.10	1.96	0.20	6.58	1.37
15 San Joaquin	2.78	2.78	0.24	5.35	1.57
16 Sonoma	2.52	2.74	0.47	6.43	1.48
17 Stanislaus	1.29	1.22	0.07	3.07	1.08
18 Santa Barbara	2.02	1.74	0.14	5.07	1.33
19 Solano	2.61	3.29	0.14	5.01	1.53
20 Tulare	1.48	1.54	0.28	2.78	1.19
21 Santa Cruz	0.49	0.51	0.16	0.82	0.69
22 Marin	0.69	0.36	0.11	1.82	0.77
23 San Luis Obispo	1.38	1.12	0.24	2.67	1.13
24 Placer	2.10	2.08	0.21	4.63	1.40
25 Merced	0.89	0.81	0.27	2.23	0.91

(continued)

Table 9-2. Design effect (DEFF) and square root DEFF (DEFT) statistics for estimates from the child interviews, overall and by reported stratum (continued)

Stratum	Design effect (DEFF)				DEFT
	Average	Median	Minimum	Maximum	Average
26 Butte	0.55	0.56	0.03	1.15	0.71
27 Shasta	0.53	0.51	0.02	1.06	0.71
28 Yolo	0.62	0.65	0.04	1.24	0.76
29 El Dorado	0.48	0.46	0.06	1.08	0.67
30 Imperial	1.14	0.85	0.04	3.37	0.98
31 Napa	0.40	0.31	0.10	1.30	0.61
32 Kings	0.49	0.46	0.06	1.07	0.67
33 Madera	0.59	0.51	0.07	1.50	0.73
34 Monterey	1.74	1.60	0.58	3.51	1.28
35 Humboldt	0.39	0.44	0.07	0.78	0.61
36 Nevada	0.17	0.17	0.00	0.40	0.39
37 Mendocino	0.33	0.34	0.04	0.45	0.57
38 Sutter	0.31	0.30	0.02	0.70	0.53
39 Yuba	0.29	0.21	0.10	0.74	0.52
40 Lake	0.35	0.35	0.07	0.64	0.57
41 San Benito	0.20	0.20	0.06	0.47	0.44
42 Tehama, etc.	0.32	0.23	0.03	0.95	0.51
43 Del Norte, etc.	0.24	0.19	0.03	0.61	0.47
44 Tuolumne, etc.	0.24	0.16	0.02	0.72	0.44

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Table 9-3. Design effect (DEFF) and square root DEFF (DEFT) statistics for estimates from the adolescent interviews, overall and by reported stratum

Stratum	Design effect (DEFF)				DEFT
	Average	Median	Minimum	Maximum	Average
State	1.64	1.73	0.15	2.24	1.27
1 Los Angeles	1.33	1.40	0.00	2.89	1.11
2 San Diego	1.39	1.30	0.29	2.94	1.15
3 Orange	2.85	2.81	1.74	4.63	1.68
4 Santa Clara	1.76	1.87	0.60	3.35	1.29
5 San Bernardino	1.88	2.24	0.02	3.06	1.32
6 Riverside	2.44	2.82	0.37	3.81	1.50
7 Alameda	1.97	1.89	0.70	3.87	1.38
8 Sacramento	1.88	2.01	0.65	3.28	1.33
9 Contra Costa	1.43	1.15	0.35	2.59	1.16
10 Fresno	1.71	1.83	0.59	2.59	1.29
11 San Francisco	1.56	1.74	0.05	3.09	1.19
12 Ventura	1.70	1.72	0.77	2.70	1.29
13 San Mateo	1.56	1.54	0.12	2.66	1.20
14 Kern	1.46	1.38	0.47	3.31	1.18
15 San Joaquin	1.50	1.49	0.83	2.79	1.21
16 Sonoma	0.49	0.38	0.13	0.98	0.67
18 Santa Barbara	1.16	1.03	0.14	2.15	1.02
19 Solano	1.40	1.74	0.14	3.00	1.09
20 Tulare	0.99	1.00	0.21	1.56	0.98
21 Santa Cruz	0.40	0.36	0.21	0.72	0.63
22 Marin	0.82	0.68	0.02	1.90	0.87
24 Placer	0.62	0.62	0.20	0.95	0.77
25 Merced	0.71	0.70	0.23	1.32	0.83
26 Butte	0.38	0.36	0.01	0.65	0.59
27 Shasta	0.26	0.18	0.01	0.78	0.45
28 Yolo	0.23	0.27	0.06	0.38	0.46

(continued)

Table 9-3. Design effect (DEFF) and square root DEFF (DEFT) statistics for estimates from the adolescent interviews, overall and by reported stratum (continued)

Stratum	Design effect (DEFF)				DEFT
	Average	Median	Minimum	Maximum	Average
29 El Dorado	0.30	0.33	0.01	0.55	0.50
30 Imperial	0.66	0.62	0.17	1.41	0.78
31 Napa	0.26	0.26	0.11	0.56	0.50
32 Kings	0.25	0.20	0.00	0.81	0.46
33 Madera	0.25	0.30	0.04	0.45	0.48
34 Monterey	1.71	1.20	0.44	3.42	1.26
35 Humboldt	0.16	0.16	0.01	0.25	0.39
36 Nevada	0.13	0.09	0.04	0.41	0.33
37 Mendocino	0.10	0.09	0.02	0.37	0.30
38 Sutter	0.29	0.26	0.11	0.48	0.53
39 Yuba	0.30	0.29	0.08	0.50	0.53
42 Tehama, etc.	0.19	0.20	0.00	0.37	0.39
44 Toulumne, etc.	0.53	0.58	0.02	0.92	0.69

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Note. Design effect estimates are only provided for strata with 10 or more adolescent interviews.

9.2 Methods for Variance Estimation

Variance estimation for CHIS comes in two forms. The first is referred to as Taylor Series linearization or *linearization* for short. The analysis weights described in Chapters 4-6 along with the design stratum indicator and survey analysis software (e.g., SUDAAN, Stata, SAS/Survey, R) are used to generate (weighted) linearized variance estimates. Design effects (variance given the design divided by the variance under a simple random sample) and coefficients of variation (standard error divided by the estimated average) can be calculated to assess the relative precision of any particular estimate.

The second form of variance estimation is replication. There are several benefits noted for replication variance estimation, including the ability to capture the random nature of the adjustments applied throughout the weighting process. Replicate point estimates (e.g., mean) are generated from replicate weights and used in the following general formula to calculate the associated variance for the point estimate:

$$\mathrm{v}(\hat{\theta}) = a \sum_{r=1}^{R} \left(\hat{\theta}_{(r)} - \hat{\theta}\right)^2 \qquad (9.2)$$

where $\hat{\theta}_{(r)}$ is the estimate generated from the *r*th replicate; $\hat{\theta}$ is the full-sample estimate generated using the main analytic weight; and a is a constant depending on the replication method chosen. R is the total number of replicates formed. Replicate weights were formed by first adjusting the base weights for the subsampling and then administering all adjustments applied to the linear weight to each replicate weight. See Wolter (2007) for a detailed discussion of variance estimation.

CHIS 2023 employed similar methodology as in past rounds of CHIS—a paired-unit grouped jackknife (GJK) replication with R=80 replicates (see, e.g., Valliant et al., 2008). Details of the CHIS replicates are provided in the next section.

9.3 Design of Replicates

Replicate variance estimation requires a set of weights that capture all components associated with the sample design and weight adjustments applied to the full-sample weight (Chapters 3-6). The sections below describe the methods for calculating the replicate weights for the one-year estimates (Section 9.3.1).

9.3.1 One-Year Replicates

A paired jackknife replication method (JK2) was used for computing variances in CHIS 2023 to maintain consistency with prior years of the study. The benefits of a replication method include, for example, the ability to reflect all components of the design and the survey weights into the estimates of precision without the need to know such information. For example, Chapters 3-6 detailed several adjustments applied to the weights to address sampling and subsampling for nonresponse and to limit biases associated with nonresponse and coverage. The replicate weights were constructed to capture potential variability in these adjustments.

Construction of the JK2 replicate weights follows procedures developed previously for CHIS. A total of 80 replicates were created to maintain the same degrees of freedom as in previous rounds of CHIS[4]. Construction of the replicates followed the following procedures:

1) Sampled addresses were sorted within sample design strata (both geographic and modeled strata) in the same order as when they were initially selected. Sampled addresses are referred to as sample units in the discussion below.
2) The ordered sample units were paired within the list and assigned to one of 80 variance strata in a circular fashion (in the JK2 method, the number of replicates is equal to the number of variance estimation strata). Once the 80th pair was assigned to variance stratum 80, the next pair was assigned to variance stratum 1 and so on. As a result, each variance stratum had approximately the same number of sample units.
3) Each sample unit in the pair was randomly assigned to variance unit (1 or 2 within each variance stratum) resulting in 2 variance units per variance stratum, each with approximately the same number of sample units.

The replicate weights were then created within each of the 80 strata that contained a random subsample of respondents, nonrespondents, ineligibles and those with unknown eligibility status. The first step was to form the replicate base weights by modifying the final base weights shown in Equations (3.1), (3.2) and (3.3):

[4] The construction of the 2023 replicate weights was the same as that used since CHIS 2019. This procedure deviated slightly from the procedures used in 2015-2018. While all years created 80 replicate weights, using the paired jackknife method, the CHIS 2015-2018 includes 80 replicates created from 40 variance strata. Due to the special nature of JK2 (relative to other delete-n Jackknife methods), creating 80 variance strata allows for the same precision one would achieve with 160 variance strata under the JK*n* methodology. This procedure is in line with the replicate weight methodology used in CHIS prior to 2015.

$$BW_i^{(r)} = \begin{cases} 2 \times BW_i, & \text{if sample unit } i \text{ in variance stratum } s \text{ and variance unit 1} \\ 0, & \text{if sample unit } i \text{ in variance stratum } s \text{ and variance unit 2} \\ BW_i, & \text{if sample unit } i \text{ not in variance stratum } s \end{cases} \quad (9.3)$$

where $s = 1,2, \dots, 80$ to index the replicate variance strata.

The same sequence of weighting adjustments used in the full sample weight is then applied to the replicate base weights to create the final replicate weights. Thus, all of the different components of the weighting process are fully reflected in the replicate weights, ranging from household adjustments (nonresponse, adjustment for household noncoverage, and adjustment to control totals) to person adjustments (nonresponse, frame compositing and raking). The final step was to calibrate the weights to the DOF population estimates used for the full sample. Thus, the weight sums for the replicates and full sample estimate the size of the CHIS target population and should match apart from rounding or deviations from the full-sample calibration model.

9.4 Software for Computing Variances

As mentioned in Chapter 2 of this report, researchers must account for the CHIS sampling design and use analysis weights to produce design unbiased population estimates. The focus of this section is a discussion of example software packages to properly accomplish this goal. Choice of software is generally user preference because they produce similar or even equivalent estimates.

- **SAS®, Version 9.4** (SAS, 2015) includes various procedures to analyze complex survey data and provide either linearization or replication variance estimates. The latter methodology is invoked with a REPWEIGHTS statement. For example, PROC SURVEYFREQ is used for categorical variables. VARMETHOD=JACKKNIFE requests the appropriate variance estimation method for CHIS.
- **Stata, Version 16** (StataCorp, 2019) is another option for analyzing CHIS data. Stata contains a list of survey procedures accessed via svy commands to analyze data from sample surveys. For example, “svy mean” and “svy total” produce estimated means and totals, respectively. Replication variance estimates are requested with “svyset” by identifying the linear weights with the “pw” option, the replicate weights with the “jkrweight” option, and the design as “vce(jack).”
- **R, Version 4.0.2** (Venables et al., 2020) is a third option for analyzing CHIS data. R is a free software and contains several packages that house procedures for analyzing survey data such

as “survey” (Lumley, 2020) and “PracTools” (Valliant et al., 2020). As with the other packages, R will generate either linearization or replication variance estimates for a variety of statistics. Design objects are first specified via the “svydesign” command to define the type of variance estimation required; “svrepdesign” is needed specifically for replication variances. Functions such as “svymean” and “svytable” then operate on the design objects to produce the associated estimates.

- **WesVar, Version 5.1** (Westat, 2007) is provided free of charge from Westat. WesVar is an interactive software program with a graphical interface that includes replication methods to compute variance estimates. Analytic capabilities include descriptive statistics, as well as multivariate linear and logistic regression.
  WesVar requires (1) the identification of the CHIS full (linear) and replicate weights provided on the data file, and (2) the specification of the replication method JK2. This allows the software to properly account for the sample design and the analysis weights.
- **SUDAAN®, Version 11** (RTI, 2012) is software developed by RTI International to analyze correlated data such as those from a survey. Estimated standard errors are available for Taylor series approximation (linearization) or for replication methods. Replication methods are recommended for CHIS to properly account for the complex nature of the analysis weights. SUDAAN contains several procedures for analyzing correlated data. For example, descriptive statistics for categorical and continuous variable are calculated with the CROSSTAB and DESCRIPT procedures, respectively. As with WesVar, SUDAAN requires (1) the identification of the CHIS linear weights (WEIGHT statement) and replicate weights (JACKWGTS statement) provided on the data file, and (2) the specification of the replication method using the DESIGN=JACKKNIFE option.

Replication variance estimates are recommended. However, the CHIS data files contain two variables that enable calculation of Taylor-series linearization standard errors.

- TSVARSTR (Taylor’s series variance stratum) – identifies the variance strata. This variable was created by sequentially numbering the design strata separately by year. TSVARSTR must be specified in the software packages when linearization standard errors are desired.
- TSVRUNIT (Taylor’s series unit) – identifies the household cluster for those with multiple person interviews. This variable was created by sequentially numbering participating households within design stratum. In contrast to TSVARSTR, TSVRUNIT is needed only for analyses involving multiple respondents per household (adult and child/adolescent, child and adolescent, or adult, child and adolescent).

10. LIMITATIONS FOR WEIGHTING AND VARIANCE ESTIMATION

The selection of weighting calibration dimensions can be a subjective process, and changes are generally minimized for historical continuity. Selecting a limited number of calibration dimensions is necessary but may not address coverage gaps or nonresponse bias across all demographic and socioeconomic characteristics.

Additionally, CHIS constructs paired Jackknife replicates (JK2), a special case of Jackknife replicate (JKn), to produce replicate point estimates. Researchers should be aware that the JK2 variance estimator has no particular theoretical support for non-linear estimators and neither JKn nor JK2 converges to the correct variance for quantiles (Valliant et al., 2013). This limitation of the statistical approach is especially relevant when comparing certain CHIS estimates to estimates from other complex surveys with different replicate weight designs.

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APPENDIX A – FRAME SIZES, SAMPLE SIZES, AND BASE WEIGHTS

Appendix A includes supplemental information on the CHIS 2023 main ABS design directly related to calculation of the base weights (inverse probability of selection).

Table A-1 contains estimated ABS frame counts across geographic and modeled strata. Table A-2 shows the amount of sample released across strata and Table A-3 shows the resulting base weights.

Table A-1. 2023 ABS estimated frame sizes

Sample Stratum	Viet	Korean	Likely Asian lang	Likely Span lang	Hisp	Other HD non-Eng	Other Asian	HD Black	HH w/ child	Other 65+	Res. match	Res. no match
1 Los Angeles	49,660	133,990	305,720	883,543	181,297	869,618	114,432	106,465	311,627	223,784	118,401	199,314
2 San Diego	16,904	17,947	72,354	198,878	53,272	189,433	44,178	16,258	227,844	174,109	76,067	106,646
3 Orange	59,268	53,910	92,388	163,921	53,246	225,779	48,508	1,815	160,689	134,254	49,438	74,942
4 Santa Clara	39,563	44,573	82,838	77,750	28,841	177,774	46,468	857	57,164	48,104	18,509	61,265
5 San Bernardino	5,624	14,109	39,216	216,376	39,731	84,621	21,812	16,838	93,921	66,152	24,774	52,459
6 Riverside	6,110	9,554	38,299	217,125	40,418	94,579	25,748	13,429	134,335	116,485	36,808	55,436
7 Alameda	15,826	29,476	71,265	68,093	23,071	171,788	41,571	41,913	52,858	39,706	18,065	37,218
8 Sacramento	11,875	11,579	40,903	73,028	22,296	119,236	30,159	19,657	99,633	76,529	32,044	43,084
9 Contra Costa	4,875	12,517	31,203	57,252	15,741	77,234	29,045	14,827	74,822	62,635	16,097	22,038
10 Fresno	2,027	4,682	18,362	95,156	22,031	60,012	12,302	4,520	41,690	32,023	12,262	23,389
11 San Francisco	8,842	24,492	49,132	25,178	9,283	75,780	18,982	4,678	52,708	24,835	26,893	61,427
12 Ventura	1,544	3,727	15,565	59,275	14,783	34,960	10,356	350	57,072	54,025	15,400	18,921
13 San Mateo	4,478	15,488	31,668	31,446	13,533	66,701	17,640	421	34,538	29,689	11,183	20,956
14 Kern	861	1,476	10,611	91,339	17,621	18,096	8,872	3,777	53,426	36,771	15,056	28,356
15 San Joaquin	3,059	3,338	15,188	58,532	13,370	49,601	15,625	3,618	37,192	25,867	9,368	16,691
16 Sonoma	796	1,260	7,404	20,907	8,730	29,195	3,823	265	42,610	44,953	15,470	20,112
17 Stanislaus	714	1,301	6,919	48,560	11,631	38,837	4,904	810	26,695	21,663	7,303	9,947
18 Santa Barbara	508	1,386	6,394	29,858	9,399	22,298	3,170	755	25,605	26,634	9,811	16,672
19 Solano	901	1,662	9,733	24,934	7,891	28,058	9,493	22,611	23,612	20,007	5,768	7,170
20 Tulare	238	556	4,390	55,560	11,253	26,231	1,897	248	17,044	12,534	3,844	10,200
21 Santa Cruz	245	826	4,222	13,508	3,962	3,610	2,325	0	23,498	22,335	9,240	12,759
22 Marin	577	1,458	4,445	5,167	3,103	13,667	2,742	0	25,964	27,046	7,837	12,455
23 San Luis Obispo	295	590	4,409	10,510	3,974	10,541	2,422	0	26,579	28,147	9,268	15,463
24 Placer	757	1,702	5,657	11,022	4,918	11,142	6,775	0	50,139	40,459	11,727	12,707
25 Merced	341	817	4,130	31,100	7,073	16,961	2,197	562	9,007	6,170	2,524	5,651
26 Butte	284	634	2,774	6,698	2,509	9,556	1,073	530	21,083	18,918	9,019	11,107
27 Shasta	138	422	1,536	3,596	1,376	3,851	699	0	21,287	21,644	8,401	9,617

(continued)

Table A-1. 2023 ABS estimated frame sizes (continued)

Sample Stratum	Viet	Korean	Likely Asian lang	Likely Span lang	Hisp	Other HD non-Eng	Other Asian	HD Black	HH w/ child	Other 65+	Res. match	Res. no match
28 Yolo	664	1,864	4,297	11,723	3,849	13,726	4,146	373	14,826	10,061	4,348	7,792
29 El Dorado	228	642	2,096	3,347	1,868	2,299	2,087	0	24,804	21,593	6,879	7,665
30 Imperial	49	303	1,620	27,732	4,596	8,227	396	0	2,704	1,523	748	3,246
31 Napa	168	349	2,281	7,841	2,474	17,769	1,028	0	7,255	7,947	2,344	4,026
32 Kings	69	237	1,624	14,463	3,471	8,266	672	762	5,704	3,249	1,272	4,458
33 Madera	67	267	1,663	15,460	3,345	2,104	959	0	8,830	8,045	2,622	5,430
34 Monterey	501	1,257	5,751	37,018	7,881	26,699	2,641	895	15,218	16,145	5,399	12,194
35 Humboldt	31	329	1,298	2,671	1,193	3,305	708	0	15,581	12,593	5,206	9,083
36 Nevada	20	234	922	1,532	754	897	569	0	13,188	15,580	4,171	6,485
37 Mendocino	76	166	938	3,116	1,055	5,869	318	0	5,521	6,576	2,246	4,723
38 Sutter	72	199	1,739	5,403	1,474	12,294	1,579	0	4,281	3,791	1,189	1,565
39 Yuba	108	385	1,359	4,384	934	3,523	866	0	6,421	3,722	1,932	3,335
40 Lake	24	95	779	2,168	925	1,855	371	214	5,041	5,421	2,142	5,330
41 San Benito	85	93	905	7,072	1,253	3,093	275	0	2,985	2,200	593	1,093
42 Tehama, etc.	36	164	1,259	6,619	2,150	4,002	508	168	8,984	8,888	3,150	5,252
43 Del Norte, etc.	39	296	1,072	2,330	1,101	1,762	429	625	11,596	12,998	5,033	10,701
44 Tuolumne, etc.	66	276	1,610	3,662	1,768	2,477	774	347	17,389	20,748	6,409	12,053

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Table A-2. 2023 sample sizes

Sample Stratum	Viet	Korean	Likely Asian lang	Likely Span lang	Hisp	Other HD non-Eng	Other Asian	HD Black	HH w/ child	Other 65+	Res. match	Res. no match
1 Los Angeles	1,456	3,235	5,329	30,276	2,817	13,111	991	4,918	5,027	818	979	1,729
2 San Diego	787	696	2,055	10,242	1,285	4,529	602	1,141	6,183	1,061	1,082	1,543
3 Orange	1,880	1,352	1,520	4,309	683	3,040	394	80	2,493	465	418	664
4 Santa Clara	1,118	1,005	1,232	1,835	335	2,130	341	33	795	148	138	479
5 San Bernardino	227	465	850	7,464	667	1,488	234	950	1,905	300	272	608
6 Riverside	234	294	765	6,887	634	1,523	255	705	2,515	480	376	582
7 Alameda	358	531	845	1,268	214	1,622	244	1,295	581	96	105	234
8 Sacramento	324	250	587	1,662	250	1,376	212	730	1,334	226	228	325
9 Contra Costa	137	282	461	1,339	180	907	210	566	1,029	188	119	173
10 Fresno	72	125	344	2,770	314	889	109	217	715	121	112	227
11 San Francisco	265	584	774	630	113	962	148	191	777	81	211	508
12 Ventura	54	105	287	1,746	217	519	93	17	981	208	143	182
13 San Mateo	133	366	494	779	165	839	135	17	503	95	87	171
14 Kern	36	49	229	3,152	300	316	95	215	1,089	162	163	324
15 San Joaquin	130	112	334	2,050	228	882	170	206	767	116	104	194
16 Sonoma	26	29	114	532	114	380	31	12	641	150	135	171
17 Stanislaus	47	61	233	2,605	312	1,072	79	70	853	147	128	179
18 Santa Barbara	25	56	172	1,272	198	478	42	53	633	143	133	230
19 Solano	31	49	178	730	112	419	85	1,073	407	77	54	69
20 Tulare	17	33	168	3,285	328	784	35	25	584	96	73	200
21 Santa Cruz	16	43	143	728	105	97	37	0	740	155	159	226
22 Marin	40	80	159	296	86	395	49	0	877	200	140	235
23 San Luis Obispo	17	26	135	500	94	256	36	0	724	171	145	231
24 Placer	42	78	160	506	110	259	101	0	1,343	240	172	194
25 Merced	35	65	224	2,656	299	730	59	78	453	69	67	159
26 Butte	26	53	144	575	106	418	29	78	1,055	209	235	298
27 Shasta	19	45	111	411	76	224	25	0	1,423	321	301	363

(continued)

Table A-2. 2023 sample sizes (continued)

Sample Stratum	Viet	Korean	Likely Asian lang	Likely Span lang	Hisp	Other HD non-Eng	Other Asian	HD Black	HH w/ child	Other 65+	Res. match	Res. no match
28 Yolo	56	128	191	824	130	499	94	42	615	86	104	184
29 El Dorado	26	60	128	322	87	108	62	0	1,394	271	212	245
30 Imperial	9	41	148	4,025	326	602	19	0	232	29	34	155
31 Napa	25	42	182	997	157	1,142	40	0	546	133	94	173
32 Kings	17	46	209	2,903	342	847	40	246	672	88	82	294
33 Madera	18	58	237	3,478	370	240	66	0	1,171	234	185	405
34 Monterey	29	58	175	1,790	184	651	39	71	428	95	85	192
35 Humboldt	5	42	110	359	80	225	29	0	1,234	220	221	402
36 Nevada	5	41	103	260	68	74	33	0	1,397	359	239	373
37 Mendocino	20	35	124	674	113	644	21	0	699	185	153	341
38 Sutter	24	50	308	1,501	199	1,768	136	0	705	136	101	148
39 Yuba	45	123	292	1,520	153	616	94	0	1,298	168	211	383
40 Lake	11	36	194	858	185	372	46	134	1,162	278	264	691
41 San Benito	36	32	204	2,401	205	537	27	0	590	98	71	119
42 Tehama, etc.	9	32	164	1,305	211	368	33	40	1,146	251	216	368
43 Del Norte, etc.	7	36	95	296	77	109	28	118	903	239	231	607
44 Tuolumne, etc.	9	34	120	417	106	151	34	51	1,166	311	239	500

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Table A-3. 2023 ABS base weights

Sample Stratum	Viet	Korean	Likely Asian lang	Likely Span lang	Hisp	Other HD non-Eng	Other Asian	HD Black	HH w/ child	Other 65+	Res. match	Res. no match
1 Los Angeles	29.71	37.11	55.17	34.98	72.20	69.20	109.54	22.04	60.98	256.28	108.06	108.06
2 San Diego	18.75	23.55	35.44	22.35	45.45	44.08	72.08	14.52	37.97	171.54	67.51	70.93
3 Orange	31.53	39.87	60.78	38.04	77.96	74.27	123.12	22.69	64.46	288.72	112.87	118.27
4 Santa Clara	35.39	44.35	67.24	42.37	86.09	83.46	136.27	25.96	71.90	325.03	127.90	134.13
5 San Bernardino	24.77	30.34	46.14	28.99	59.57	56.87	93.22	17.72	49.30	220.51	86.28	91.08
6 Riverside	26.11	32.50	50.06	31.53	63.75	62.10	100.97	19.05	53.41	242.68	95.25	97.89
7 Alameda	44.21	55.51	84.34	53.70	107.81	105.91	170.37	32.37	90.98	413.60	159.05	172.05
8 Sacramento	36.65	46.32	69.68	43.94	89.18	86.65	142.26	26.93	74.69	338.62	132.57	140.54
9 Contra Costa	35.58	44.39	67.69	42.76	87.45	85.15	138.31	26.20	72.71	333.16	127.39	135.27
10 Fresno	28.15	37.45	53.38	34.35	70.16	67.51	112.87	20.83	58.31	264.65	103.03	109.48
11 San Francisco	33.37	41.94	63.48	39.97	82.15	78.77	128.25	24.49	67.83	306.61	120.92	127.45
12 Ventura	28.60	35.49	54.23	33.95	68.12	67.36	111.36	20.59	58.18	259.74	103.96	107.70
13 San Mateo	33.67	42.32	64.11	40.37	82.02	79.50	130.67	24.74	68.66	312.52	122.55	128.54
14 Kern	23.91	30.12	46.34	28.98	58.74	57.26	93.39	17.57	49.06	226.98	87.52	92.37
15 San Joaquin	23.53	29.81	45.47	28.55	58.64	56.24	91.91	17.56	48.49	222.99	86.04	90.08
16 Sonoma	30.60	43.44	64.95	39.30	76.58	76.83	123.34	22.10	66.47	299.69	117.61	114.60
17 Stanislaus	15.20	21.32	29.69	18.64	37.28	36.23	62.08	11.57	31.30	147.37	55.57	57.05
18 Santa Barbara	20.31	24.75	37.18	23.47	47.47	46.65	75.47	14.24	40.45	186.25	72.49	73.77
19 Solano	29.07	33.92	54.68	34.16	70.45	66.97	111.68	21.07	58.02	259.84	103.91	106.81
20 Tulare	14.02	16.85	26.13	16.91	34.31	33.46	54.20	9.93	29.18	130.57	51.00	52.65
21 Santa Cruz	15.30	19.21	29.53	18.56	37.74	37.22	62.85	NA	31.75	144.10	56.45	58.11
22 Marin	14.43	18.22	27.96	17.46	36.08	34.60	55.96	NA	29.61	135.23	53.00	55.98
23 San Luis Obispo	17.35	22.69	32.66	21.02	42.28	41.18	67.27	NA	36.71	164.60	66.94	63.92
24 Placer	18.01	21.82	35.36	21.78	44.71	43.02	67.08	NA	37.33	168.58	65.50	68.18
25 Merced	9.75	12.58	18.44	11.71	23.66	23.23	37.23	7.20	19.88	89.43	35.54	37.67
26 Butte	10.94	11.95	19.26	11.65	23.67	22.86	37.01	6.80	19.98	90.51	37.27	38.38
27 Shasta	7.28	9.38	13.84	8.75	18.10	17.19	27.96	NA	14.96	67.43	26.49	27.91

(continued)

Table A-3. 2023 ABS base weights (continued)

Sample Stratum	Viet	Korean	Likely Asian lang	Likely Span lang	Hisp	Other HD non-Eng	Other Asian	HD Black	HH w/ child	Other 65+	Res. match	Res. no match
28 Yolo	11.85	14.56	22.50	14.23	29.61	27.51	44.10	8.88	24.11	116.99	42.35	41.81
29 El Dorado	8.78	10.70	16.37	10.39	21.47	21.28	33.67	NA	17.79	79.68	31.29	32.45
30 Imperial	5.42	7.40	10.95	6.89	14.10	13.67	20.82	NA	11.66	52.51	20.94	22.00
31 Napa	6.73	8.31	12.53	7.86	15.76	15.56	25.71	NA	13.29	59.75	23.27	24.93
32 Kings	4.07	5.14	7.77	4.98	10.15	9.76	16.81	3.10	8.49	36.92	15.16	15.52
33 Madera	3.70	4.60	7.02	4.45	9.04	8.77	14.53	NA	7.54	34.38	13.41	14.17
34 Monterey	17.26	21.67	32.86	20.68	42.83	41.01	67.72	12.60	35.56	169.95	63.51	63.52
35 Humboldt	6.21	7.84	11.80	7.44	14.91	14.69	24.42	NA	12.63	57.24	22.59	23.56
36 Nevada	4.10	5.70	8.95	5.89	11.09	12.12	17.26	NA	9.44	43.40	17.39	17.45
37 Mendocino	3.78	4.75	7.56	4.62	9.34	9.11	15.13	NA	7.90	35.54	13.85	14.68
38 Sutter	3.00	3.98	5.65	3.60	7.41	6.95	11.61	NA	6.07	27.88	10.58	11.77
39 Yuba	2.40	3.13	4.65	2.88	6.11	5.72	9.21	NA	4.95	22.16	8.71	9.15
40 Lake	2.22	2.63	4.01	2.53	5.00	4.99	8.06	1.60	4.34	19.50	7.71	8.11
41 San Benito	2.37	2.90	4.44	2.95	6.11	5.76	10.19	NA	5.06	22.45	9.18	8.35
42 Tehama, etc.	3.97	6.10	8.55	5.54	11.11	10.75	14.83	4.21	9.44	41.72	16.19	16.72
43 Del Norte, etc.	5.03	6.53	8.61	6.54	12.74	14.70	12.49	5.35	10.88	48.41	19.79	19.78
44 Tuolumne, etc.	7.82	7.15	11.24	7.53	14.87	15.52	20.52	6.80	12.93	58.62	22.56	23.95

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

*Note: Geographic strata 1, 2, 42, 43 and 44 were divided into geographic substrata. The base weights presented in Table A-3 are averages across all substrata.

APPENDIX B – SUMMARY STATISTICS FOR WEIGHTS AND WEIGHT ADJUSTMENTS

Appendix B includes summary statistics on the CHIS 2023 base weights, analysis weights, and the weight adjustments by person interview (adult, child and adolescent).

Table B-1 contains summary statistics for the household weight (Chapter 3) used as the basis for the person-level weights.

Table B-2, Table B-3, and Table B-4 includes summary information for the adult weights (Chapter 4), child weights (Chapter 5) and adolescent weights (Chapter 6).

Table B-1. Screener interview (households) weighting adjustments

Survey Weight Statistics (Household table)	ABS	PPD Cell	LBC OS
1. Base weight			
1.1 Sample size	321,927	150,648	7,386
1.2 Sum of weights	13,794,155	9,356,568	177,600
1.3 Coefficient of variation	94.4	36.9	81.3
2. Unknown residential status adjustment			
2.1 Sample size			
a. Known residential status	160,240	93,723	3,865
b. Unknown residential status	161,687	56,925	3,521
2.2 Sum of weights	12,691,836	9,321,562	164,458
2.3 Coefficient of variation	168.0	39.6	149.7
2.4 Mean non-zero adjustment factor	1.76	1.61	1.72
3. Screener nonresponse adjustment			
3.1 Sample size			
a. Screener respondents	31,184	6,547	737
b. Screener nonrespondents	123,016	86,244	3,008
3.2 Sum of weights	12,432,032	4,003,999	161,350
3.3 Coefficient of variation	99.2	37.5	88.9
3.4 Mean non-zero adjustment factor	4.43	5.99	4.90
4. Calibration to Low Response Score			
4.1 Sample size	31,184	NA	NA
4.2 Sum of weights	13,044,266	NA	NA
4.3 Coefficient of variation	97.8	NA	NA

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Table B-2. Extended adult interview weighting adjustments

Survey Weight Statistics (Adult table)	ABS	PPD Cell	LBC OS
1. Number of Adults Adjustment			
1.1 Sample size	31,184	2,556	737
1.2 Sum of weights	25,043,065	1,553,378	297,776
1.3 Coefficient of variation	100.6	38.1	107.2
1.4 Mean non-zero adjustment factor	2.01	0.39	1.85
2. Adult nonresponse adjustment			
2.1 Sample size			
a. Adult respondents	20,556	621	494
b. Adult nonrespondents	10,628	1,935	243
2.2 Sum of weights	25,043,065	1,553,378	297,776
2.3 Coefficient of variation	122.0	59.8	95.0
2.4 Mean non-zero adjustment factor	1.5	4.3	1.5
3. Adult composite adjustments	ABS+PPD Cell+LBC		
3.1 Sample size	21,671		
3.2 Sum of weights	24,777,350		
3.3 Coefficient of variation	124.5		
3.4 Mean adjustment factor	0.94		
4. Pre-calibration trimming	ABS+PPD Cell+LBC		
4.1 Sample size	21,671		
4.2 Number of records trimmed	786		
4.3 Sum of weights	23,833,684		
4.4 Coefficient of variation	96.6		
5. Final Calibration Adjustment	ABS+PPD Cell+LBC		
5.1 Sample size	21,671		
5.2 Sum of weights	29,210,979		
5.3 Coefficient of variation	148.7		
5.4 Mean weight	1,347.93		

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Table B-3. Extended child interview weighting adjustments by sample type

Survey Weight Statistics (Child table)	ABS	PPD Cell	LBC OS
1. Base weight			
1.1 Sample size	4,106	221	77
1.2 Sum of weights	2,905,296	201,864	30,479
1.3 Coefficient of variation	117.4	78.2	101.7
2. Child nonresponse adjustment			
2.1 Sample size			
a. Child respondents	3,203	108	66
b. Child nonrespondents	903	113	11
2.2 Sum of weights	2,903,488	198,530	30,479
2.3 Coefficient of variation	118.6	74.9	103.6
2.4 Mean non-zero adjustment factor	1.33	1.93	1.21
3. Child composite adjustments	ABS+PPD Cell+LBC		
3.1 Sample size	3,377		
3.2 Sum of weights	2,906,680		
3.3 Coefficient of variation	118.0		
3.4 Mean adjustment factor	0.953		
4. Pre-calibration trimming	ABS+PPD Cell+LBC		
4.1 Sample size	3,377		
4.2 Number of records trimmed	126		
4.3 Sum of weights	2,794,433		
4.4 Coefficient of variation	99.5		
5. Final Calibration Adjustment	ABS+PPD Cell+LBC		
5.1 Sample size	3,377		
5.2 Sum of weights	5,692,578		
5.3 Coefficient of variation	139.0		
5.4 Mean weight	1,685.69		

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.

Table B-4. Extended adolescent interview weighting adjustments by sample type

Survey Weight Statistics (Adolescent table)	ABS	PPD Cell	LBC OS
1. Base weight			
1.1 Sample size	3,335	128	55
1.2 Sum of weights	2,039,422	112,706	18,214
1.3 Coefficient of variation	107.2	62.1	88.8
2. Adolescent nonresponse adjustment			
2.1 Sample size			
a. Adolescent respondents	939	12	17
b. Adolescent nonrespondents	2,396	116	38
2.2 Sum of weights	2,039,422	66,261	18,214
2.3 Coefficient of variation	96.0	79.8	96.9
2.4 Mean non-zero adjustment factor	3.79	7.41	5.02
3. Adolescent composite adjustments	ABS+PPD Cell+LBC		
3.1 Sample size	968		
3.2 Sum of weights	1,973,097		
3.3 Coefficient of variation	99.0		
3.4 Mean adjustment factor	0.95		
4. Pre-calibration trimming	ABS+PPD Cell+LBC		
4.1 Sample size	968		
4.2 Number of records trimmed	90		
4.3 Sum of weights	1,900,107		
4.4 Coefficient of variation	88.4		
5. Final Calibration Adjustment	ABS+PPD Cell+LBC		
5.1 Sample size	968		
5.2 Sum of weights	3,143,240		
5.3 Coefficient of variation	108.7		
5.4 Mean weight	3,247.15		

Source: UCLA Center for Health Policy Research, 2023 California Health Interview Survey.