Technical Documentation for Health Resources Service Administration's Health Workforce Simulation Model

Health Resources and Services Administration

Bureau of Health Workforce

National Center for Health Workforce Analysis

Version 4.2020

HRSA Health Workforce

The Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services (DHHS), provides national leadership in the development, distribution, and retention of a diverse, culturally competent health workforce that can adapt to the population's changing health care needs and provide the highest-quality care for all. The Agency administers a wide range of training grants, scholarships, loans, and loan repayment programs that strengthen the health care workforce and respond to the evolving needs of the health care system.

The National Center for Health Workforce Analysis (the National Center), within the Bureau of Health Workforce, informs public and private sector decision-making on the U.S. health workforce by expanding and improving health workforce data and its dissemination to the public, improving and updating projections of the supply of and demand for health workers, and conducting analyses of issues important to the health workforce.

For more information about the National Center, e-mail us at healthworkforcecenter@hrsa.gov or visit our website.

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Contents

Exhibits

Acronyms Used in This Report

AAMFT	American Association for Marriage and Family Therapy
AANP	American Association of Nurse Practitioners
AAPA	American Academy of Physician Assistants
AAPT	American Association of Pharmacy Technicians
AARC	American Association for Respiratory Care
ACA	Affordable Care Act
ACA	American Chiropractic Association
ACO	Accountable Care Organization
ACS	American Community Survey
ADA	Academy of Doctors of Audiology
ADA	American Dental Association
AHCA	American Health Care Association
AMA	American Medical Association
AOA	American Optometric Association
AOTA	American Occupational Therapy Association
APA	American Psychiatric Association
APA	American Psychological Association
APMA	American Podiatric Medical Association
APN	Advanced practice nurse
APNA	American Psychiatric Nurses Association
APP	Advanced practice provider
ASCA	American School Counselor Association
ASRT	American Society of Radiologic Technologists
BLS	Bureau of Labor Statistics
BRFSS	Behavioral Risk Factor Surveillance System
CBO	Congressional Budget Office
CDC	Centers for Disease Control and Prevention
CMS	Centers for Medicare and Medicaid Services
CPNP	College of Psychiatric and Neurologic Pharmacists
DHHS	U.S. Department of Health and Human Services
DHPSA	Dental Health Professional Shortage Area
ED	Emergency department
FTE	Full time equivalent
HRSA	Health Resources and Services Administration
HPSA	Health Professional Shortage Areas
HUD	(U.S. Department of) Housing and Urban Development
HWSM	Health Workforce Simulation Model
IPEDS	Integrated Postsecondary Education Data System
ISPOR	International Society for Pharmacoeconomics and Outcomes Research
LOS	Length of stay
LPN	Licensed Practical/Vocational Nurse
LTSS	Long term services and support
MCBS	Medicare Beneficiary Survey
MDS	CMS's Nursing Home Minimum Data Set
MEPS	Medical Expenditure Panel Survey
NAADAC	Association for Addiction Professionals
NAMCS	National Ambulatory Medical Care Survey
NBCC	National Board for Certified Counselors

NCCPA	National Commission on Certification of Physician Assistants
NCES	National Center for Education Statistics
NCLEX	National Council Licensure Examination
NHAMCS	National Hospital Ambulatory Medical Care Survey
NHATS	National Health and Aging Trends Study
NHHCS	National Home and Hospice Care Survey
NIS	National Inpatient Sample
NLN	National League for Nursing
NMW	Nurse midwife
NNHS	National Nursing Home Survey
NP	Nurse practitioner
NPI	National Provider Identification
NPPES	National Plan and Provider Enumeration System
NREMT	National Registry of EMTs
NSDUH	National Survey on Drug Use and Health
NSSRN	National Sample Survey of Registered Nurses
OES	Occupational Employment Statistics
PA	Physician assistant
PCMH	Patient-centered medical home
RN	Registered nurse
SAMHSA	Substance Abuse and Mental Health Services Administration
SNF	Skilled nursing facility
SNMMI	Society of Nuclear Medicine and Molecular Imaging
SUD	Substance use disorder
WRVU	Work relative value unit

I. Introduction

The Health Workforce Simulation Model (HWSM) is an integrated microsimulation model that estimates the current and future supply of and demand for health care workers by occupation, geographic area, and year. Demand projections also are modeled by employment setting. HWSM was designed to produce national and state-level workforce projections and, starting in 2019, HWSM produces county-level projections that can be aggregated to the state and national level for purposes of modeling health workforce across urban-rural classifications. HWSM models the implications of changing demographics on health workforce supply and demand, as well as trends and policies affecting care use and delivery.

The purpose of workforce modeling is to understand the implications of trends affecting health workforce supply and demand, and whether full-time equivalent (FTE)[a] supply will be adequate to meet demand. The gap between supply and demand is often referred to as a shortage if demand exceeds supply, or as a surplus (or excess capacity) if supply exceeds demand. Such information promotes efficient allocation of resources by aiding stakeholders in decisions regarding the number of health workers to train and by informing career decisions of individuals regarding whether to enter a particular health occupation or specialty.

Workforce demand is defined as the number of health workers required to provide a level of services that will be utilized given patient health-seeking behavior and ability and willingness to pay for health care services. Training more health workers than required to provide the level of care sought by patients (i.e., excess capacity) can have detrimental consequences for providers seeking fulfillment in their career, while training too few health workers (i.e., shortage) reduces access to care—especially for historically underserved and vulnerable populations—and contributes to burnout among existing healthcare workers. As discussed later, demand is different from need, with demand reflecting the level of care that people are likely to use in the absence of supply constraints while need is a clinical definition.

Starting year supply is estimated based on the number of people active in the workforce, which consists of people working and people actively seeking employment, and reflects estimates of hours worked to calculate FTEs.[a] Estimates of active supply and FTE supply generally are lower

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[a] For modeling, we measure both supply and demand in terms of full-time equivalents (FTEs), and unless otherwise specified throughout this report demand is used synonymous with "FTE demand" and supply is used synonymous with "FTE supply." An FTE has been defined as working 40 hours per week since the year 2017; prior studies used average weekly hours worked within a profession to define an FTE, so the definition varied by profession. Hence, estimates of FTE supply will differ from other supply metrics such as licensed supply or active supply, or estimates that use a different definition for FTE.

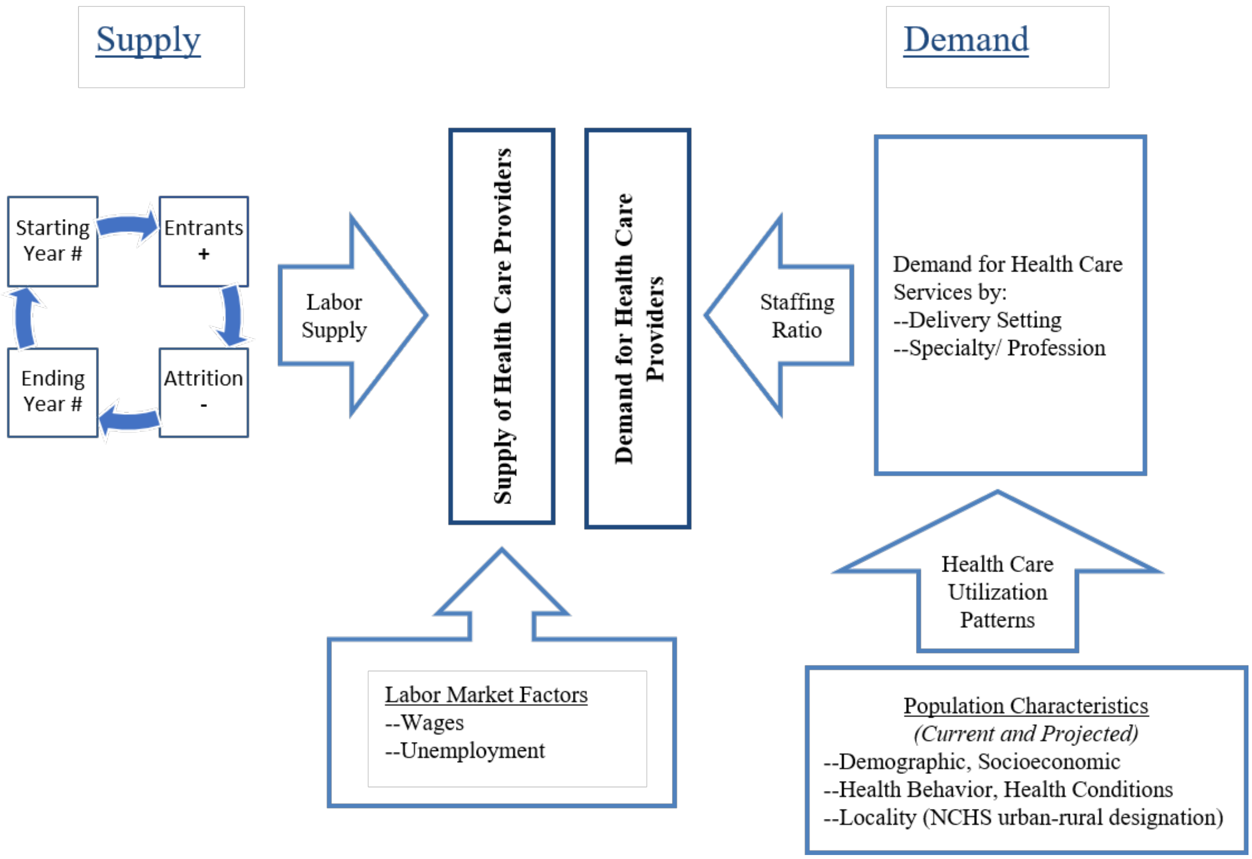
than estimates of licensed supply (for occupations requiring a license) or number of trained workers (for health occupations that do not require a license) because some individuals who are licensed and trained choose not to participate in the labor force. HWSM models the number of individuals trained each year who enter the workforce, so the supply projections are estimates of total number of people trained to provide services. Projections of total people trained might be greater than total employment for an occupation.

HWSM uses a microsimulation approach to supply modeling, meaning that individual health workers are modeled with data obtained from associations (e.g., American Medical Association Masterfile, American Dental Association Masterfile), national surveys with a representative sample of health workers (e.g., American Community Survey), and state licensure files as available. For supply modeling, HWSM simulates the current workforce and labor force participation decisions to project how supply will evolve over time. The projections reflect estimates and assumptions of the annual number and characteristics of newly trained workers entering a given occupation, and prediction equations that describe workforce attrition probabilities and weekly number of hours worked.

While the nuances of modeling differ for individual health professions and medical specialties, the basic framework used within HWSM remains the same and consists of three components: 1) the **model for supply of health professionals,** 2) the **model for demand for health care services**, and 3) the **staffing ratios** that convert demand for services to demand for health care workers (Exhibit 1). To project the number and characteristics of future health care workers and service users, HWSM simulated individual-level data based on predicted probabilities estimated from the current or base year data. Depending on the predicted probabilities, individual records were simulated to age forward. The aged individual-level records were then aggregated to obtain the projections by geographic area. On the service use side, the current utilization rates by individual characteristics were applied to projected populations at the national and state levels.

The approach for modeling demand starts with constructing a database that contains characteristics for each person in a representative sample of the population in each county and state over time. Prediction equations model the expected demand for health care services based on each person's characteristics: demographics, health risk factors including smoking and obesity, presence of diseases such as diabetes and cardiovascular disease, among others, and economic considerations including whether the person has health insurance and level of household income. Demand for health care services is then used to model health workforce demand.

Exhibit 1: HRSA's Health Workforce Simulation Model



HWSM models future supply and demand under different scenarios reflecting trends and assumptions about key supply and demand determinants. All scenarios reflect changing demographics—e.g., supply accounts for aging of the health workforce and differences between men and women in labor force participation, and demand accounts for population growth and aging. Additional supply scenarios model the sensitivity of projections to trends in early or delayed retirement, and training more or fewer health workers compared to current levels. Additional scenarios around health workforce demand reflect estimates of how patient health care use might change if barriers to accessing care were removed, or how demand and/or supply might change as a result of the latest developments and trends in our evolving healthcare delivery system.

Demand for health workers is based on projections of the level of health care services that patients will use and how the staffing is configured to deliver care. The "status quo" demand projections extrapolate current national health care use and delivery patterns by personal characteristics to the state and county level[a] hypothetical populations into the future, where these hypothetical future populations' demographics, disease prevalence, economic factors, and other health risk factors reflect the expected changes in these factors by county/state and year. Therefore, demand estimates for each state reflect what demand would be for the population in that state if each person used the national average level of care for a like person (same demographics, same health risk factors, same presence of disease, same rurality[b] of residence, and same household income and insurance status).

Extrapolating current national patterns of care use and delivery does not imply that current patterns of care use and delivery are optimal or even efficient. This scenario simply reflects the realities of the current health care system and economic considerations—including medical technology, health policy, insurance coverage, prices for health care services, reimbursement rates to providers, cultural norms, and other factors that affect care use and delivery. Status quo projections of future demand reflect the number and mix of health workers that would be required if we continue to use and deliver care according to current patterns. Alternative scenarios quantify future demand for health workers if care use and delivery patterns change. Comparison of status quo to alternative demand scenarios provides insights on the contribution of population growth and aging to future demand for health workers versus the contribution of other factors that might change how care is used or delivered (for example, if dental schools started training more dentists or population health programs improved their patients' overall health).

Current health care use and delivery patterns reflect the current supply of health workers. Hence, for many occupations modeled using HWSM FTE national demand equals national supply in the base year. This approach is common across health workforce models.[2] In HWSM there are several occupation groups where national demand is calculated to be higher than national supply in the base year—primary care physicians, psychiatrists, and general surgeons. For these occupations there is great concern of national shortfalls and also external evidence of substantial under-supply in many geographic areas as corroborated by the Health Resources and Services Administration's (HRSA) efforts to define health professional shortage areas (HPSAs).[3–6] The demand projections for primary care physicians and psychiatrists use estimates of the number of providers required to remove HPSA designations as the starting year shortfall, while the general

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[a] County level estimates were generated only for oral health professions, general surgeons, and behavioral healthcare workers as of 2019.

[b] Before 2019, this was MSA versus non-MSA; after 2019 this was stratified by the six classifications in NCHS's Urban Rural Classification System.[1] In this classification scheme, counties are classified (from highest to lowest population density) as "Large central metro," "Large fringe metro" (which NCHS notes is a proxy for suburban), "Medium metro," "Small metro", "Micropolitan", and "Non-core".

surgeon shortfall national estimate models assumptions of adequate supply in urban areas but undersupply in rural areas. The specifics of the shortfall assumptions and data sources are described later in sections of this report that describe how HWSM was adapted to individual health occupations and medical specialties.

For many occupations (e.g., psychiatrists, psychologists, and other types of behavioral healthcare providers) there is concern about substantial unmet need—that is, patients have a clinical need for care but do not receive the level of care that either they or a health provider considers appropriate. Unmet need can occur for many reasons, including: (a) supply access barriers where there is no provider within a reasonable distance to the patient; (b) financial access barriers where either the patient does not have the ability to pay for services or where providers do not accept the patient's insurance; and (c) patients choosing not to seek care because of stigma, cultural norms, they do not feel care is warranted, they are too busy, or other reasons. For some occupations, demand for health workers is modeled under a scenario that reflects how demand might change if access barriers were removed. Past studies have sometimes referred to this as an "unmet needs" scenario or as a "health care utilization equity" scenario depending on the assumptions and methods used to calculate this scenario. The rationale for this scenario is the desire to build a workforce to meet the future needs of a health care system that delivers on national goals to improve access to affordable, high quality care.

HWSM consists of self-contained modules that describe different components of the health care system, which is consistent with best practices for modeling complex systems.[7] HWSM runs using R software. HWSM continues to be maintained and refined with new occupations added periodically and scenario modeling capabilities enhanced. Each year the model is used to project supply and demand for a selected set of occupations and updated with the most recent data from key data sources; as such, recently modeled occupations use more current data than occupations modeled in previous years. Substantial efforts continue to make HWSM transparent and peer-reviewed, with feedback used to refine HWSM inputs and assumptions.

The remainder of this report documents the logic, methods, data, assumptions, and validation processes for HWSM in general, and how the model was adapted to individual health occupations. Chapters II and III, respectively, describe the supply and demand components of HWSM. Chapters IV through X provide information specific to the modeled health occupation categories. Chapter XI describes model strengths, limitations, and validation activities. Other reports and fact sheets published by HRSA summarize model supply and demand projections by occupation.[8]

II. Modeling Supply of Health Professionals

The supply component of HWSM links individual and labor market characteristics to health care workers' labor supply decisions (Exhibit 2). After the base year, data are trended forward one year and those estimates become the starting point for the subsequent year with the process repeated annually over the projection period.

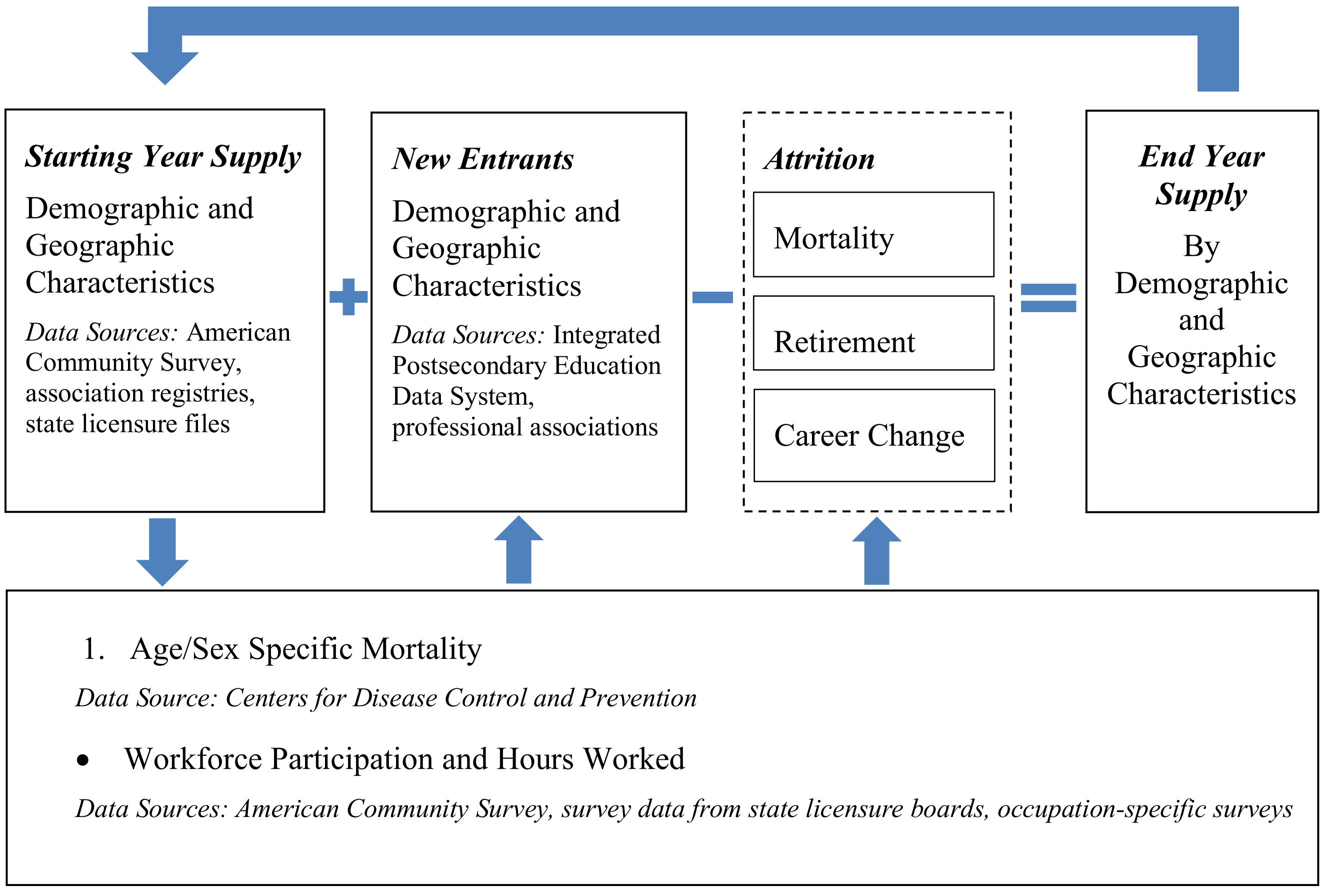
Supply projections under the "Status Quo" scenario assume that the current patterns of retirement and hours worked remain unchanged within a given age and sex group across the projection period, and that the baseline age and sex distribution of new entrants to the occupation is the same for all new entrant cohorts in the future. Under this scenario, supply changes over time are due solely to the changing demographic composition of the workforce and number of new workers trained. Alternative scenarios model the sensitivity of projections to assumptions regarding numbers of workers trained, retirement patterns, and hours worked patterns.

In general, inputs to the supply models are specific to the occupation modeled. However, for some occupations and specialties with small sample size and other data limitations, information on occupational categories or similar occupations were used in place of occupation-specific data.

Status Quo HWSM supply projections assume:

1. Present age and sex distribution of new entrants will be retained in the future
2. Present patterns of retirement and hours worked will remain unchanged within a given age and sex group

Exhibit 2: Flow Diagram for the Supply Component of HWSM



A. Estimating Base Year Supply of Active Health Professionals

The starting year supply database in HWSM contains unique records representing each person active in the health workforce. Developing a database of active supply differs slightly by occupation and geographic location based on data source, but in general active supply consists of people who are employed or who are actively seeking employment. For occupations which have national registries (e.g., physicians and dentists) with robust data describing individual characteristics, these registries were used and starting supply was defined as individuals with an active license and no indication of retirement. For physicians, the AMA Masterfile further defines an active physician as one who works 20 or more hours per week in their profession. For occupations where the starting year[a] supply data are estimated from surveys (e.g., nurses[b], technologists and technicians), records for each survey participant who is active in the workforce were replicated according to their sample weight in the survey file. For example, if a person's record in the American Community Survey (ACS) has a sample weight of 100 (indicating the record represents 100 people in that particular occupation), 100 identical records were created. Creating a record for each person is important because unique probabilities associated with labor force decisions are used for each simulated person. In states with smaller population, where the sample size is small, the creation of multiple records helped "smooth" the impact of individual characteristics on labor supply decisions such as retirement. For these smaller states, samples were drawn not only from that small state but from the state's Census District. A few occupations (such as psychologists) use a hybrid of these approaches. If national or state counts of providers are available but demographic information on these providers is not available, then the starting population is created by sampling the occupation from the ACS using the survey weights with the number of samples determined by the national or state counts. Examples of data sources for counts of providers includes the Occupational Employment Statistics (OES) as well as occupation-specific data from licensing agencies or professional associations.

All the occupations modeled use individual characteristics (age and sex, and sometimes race-ethnicity) to model labor force decisions. There are some nuances by occupation (for example, education level is modeled for nurses), and such nuances are described in sections covering specific occupations. Some occupations also use labor market characteristics associated with their state from the Bureau of Labor Statistics (BLS), namely overall state unemployment rate and average professional wages, as inputs to modeling labor force participation.

B. Modeling New Entrants to the Workforce

Simulating new entrants to the workforce is achieved via the creation of a "synthetic" cohort based on the number and characteristics of recent entrants in each occupation. First, HWSM calculates the distribution of geography, age, sex, and race from the base year distribution of those characteristic in the population of new entrants. HWSM then creates a record for each new entrant in the supply data and generates a series of random numbers. Depending upon the value of the random number and the probability of having a characteristic, the individual is assigned

[a] In different years' updates, different base (or starting) years were used, as detailed in occupation category specific categories below.

[b] For registered nurses and licensed practical nurses, some states provided data from licensure files and for all other states the starting supply data come from the American Community Survey.

that characteristic. This process is used to create for each year of the simulation a new supply cohort that reflects the distribution of characteristics seen in recent graduates from health training programs.

Data used to estimate the number and characteristics of new entrants depend on the occupation being modeled (see Chapters IV through X). Estimates on the number and characteristics of new entrants in each occupation over the forecast period are made under the assumption that current patterns continue throughout the projection period—except for select occupations where there is information on projected expansion of the educational capacity. New entrants to the workforce are defined as individuals who have completed the requirements to practice in their field.

For some occupations, the estimated number of people trained each year minus the estimated number of people who retire each year suggests a net growth in employment that is higher than actual employment level changes reflected in data sources such as OES or ACS. If the number of new entrants exceeds available employment opportunities, then supply for this occupation could exceed actual employment levels or health workers could find themselves under-employed. One example is school counselors, where annual supply growth is substantially below the growth that one would expect based on the annual number of individuals completing training as a school counselor. For this occupation, it is possible that individuals newly trained as school counselors end up not practicing as a school counselor either because they are unable to obtain employment as a school counselor or because of compensation or other reasons end up working in positions other than that of a school counselor.

C. Estimating Worker Attrition

Health care workers may leave their current occupations because of retirement, career change, or mortality. The probability of each representative worker dying during a given year was determined using mortality rates by age and sex obtained from the Centers for Disease Control and Prevention (CDC), accounting for the fact that age-adjusted mortality rates through age 65 for professional and technical occupations are approximately 25 percent lower than overall national rates for men and 15 percent lower for women.[9,10]

For many occupations, among those representative workers still living the probability of continuing to work in the initial occupation each subsequent projection year is modeled using estimates derived from analysis of the ACS. However, workforce participation probabilities for physicians, by specialty, and a limited number of occupations were modeled using occupation-specific survey data as described in the individual Chapters covering those occupations. Analysis of actual retirement patterns or of intention to retire obtained through surveys or analysis of licensure files is the preferred method for estimating retirement patterns when that data is available.

Because the ACS does not list the occupation of individuals who have been retired for more than five years, occupation-specific labor force participation rates were imputed for workers over age 50—many of whom may have retired more than five years ago. The approach for modeling attrition probabilities in HWSM has evolved over the years. Earlier studies calculated attrition rates based on ACS by analyzing net changes in the age distribution of older workers in each occupation to calculate probability of exiting the workforce. Starting in 2018, HWSM began using the ACS question that asks respondents about their workforce participation one year prior to completing the survey. Using this along with the question about current workforce participation, HWSM identifies respondents who participated in the workforce a year ago but do not currently participate, which are assumed to be retirees. The main rationale for moving to this new approach is that each year of ACS data involves a different sample of individuals and comparing the age distribution of subsequent years of samples is subject to fluctuations in sample size for individual age groups—especially at older ages. The distribution of observed retirements by age is recorded to be used in the simulation to model attrition in future years. This applies only to individuals age 50 and older—as younger workers will often exit and then re-enter the workforce. If people change occupations this information is not captured in ACS, as occupation only is provided for current occupation and not occupation in previous years.

In general, data limitations prohibit express modeling of career changes within HWSM. However, as discussed in Chapter IX, progression from licensed practical nurse (LPN) to registered nurse (RN), and from RN to advanced practice nurse (APN) are modeled for nursing supply.

D. Hours Worked and FTE Supply

Where available, hours worked reflects patient care hours; otherwise, hours worked reflects total professional hours. For physicians, the data for modeling hours worked patterns came from surveys covering the period 2012-2017 from four states: FL, MA, NY and SC. The primary benefit from using data from these states, rather than the ACS for which weekly hours worked patterns for many health occupations were modeled, is that the state data include physician specialty and have large sample sizes (as the state data was collected from physicians at time of physician re-licensure). Use of this data allowed for specialty-specific hours worked prediction equations for physicians.

For other occupations modeled, we analyzed the 5-year ACS files using Ordinary Least Squares regression. The dependent variable was number of hours worked per week by each individual active in their profession. Explanatory variables included age group and sex. For occupations where the ACS was used to model hours worked patterns, we also include a year indicator. Race and ethnicity are also explanatory variables when available using the following four categories: non-Hispanic white, non-Hispanic black, non-Hispanic other, and Hispanic.

HWSM uses the estimated regression equations to calculate each worker's expected weekly hours worked based on age, sex, and other characteristics or variables in the model. The estimated hours worked for each person are divided by 40 calculate FTE supply for each year. Prior to 2017, FTE was defined based on the national average weekly hours worked for a profession. Hence, the definition of FTE was profession specific.

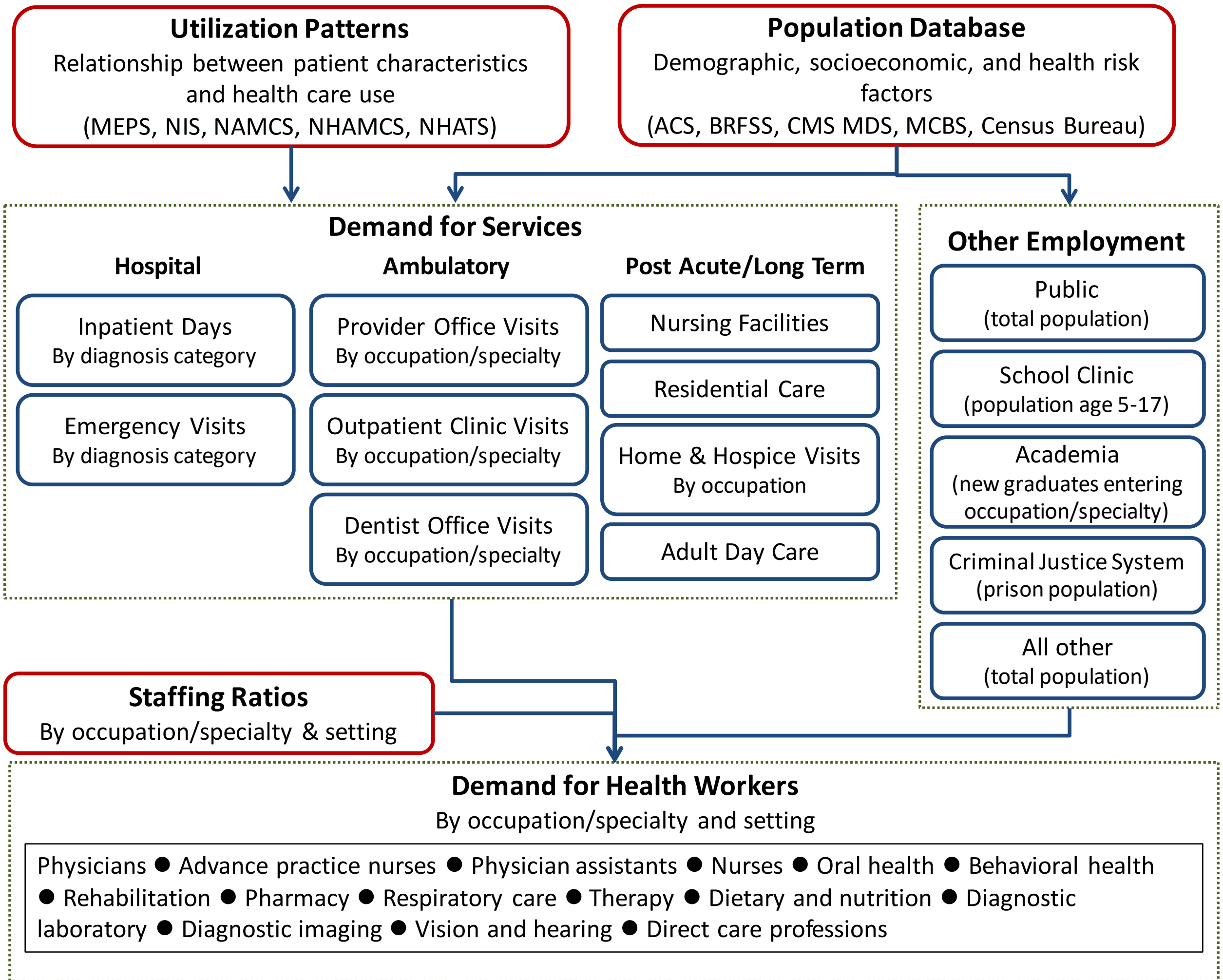
III. Modeling Demand for Health Care Services and Providers

HWSM models demand using three major elements:

- **Population databases** that contain demographic, socioeconomic, health status and health behavior information for a representative sample of the current and projected future population in a geographic area (county, state, national).
- **Regression equations** relating an individual's demographic, socioeconomic, health status and health risk factors to health service utilization by both care delivery setting and health occupation or medical specialty.
- **Staffing patterns** that convert demand for services to demand for providers.

Exhibit 3 presents a flow diagram for the demand component of HWSM, although not all care delivery sites pertain to every health occupation modeled. In this chapter we describe each of these three major elements.

Exhibit 3: Flow Diagram for the Demand Component of HWSM



Sources: MEPS=Medical Expenditure Panel Survey; NIS=National Inpatient Sample; NAMCS=National Ambulatory Medical Care Survey; NHAMCS=National Hospital Ambulatory Medical Care Survey; NHATS= National Health and Aging Trends Study; ACS=American Community Survey; BFRSS=Behavioral Risk Factor Surveillance System; CMS MDS = Centers for Medicare and Medicaid Services Long Term Care Minimum Dataset; MCBS=Medicare Beneficiary Survey; population projections come from states and the U.S. Census Bureau.

A. Construction of the Population Databases

The microsimulation approach—where demand for health care services is modeled separately for individual people—requires individual level (micro) data on the predictors of health care use for each person in a representative sample of a designated geographic region (national, state, or county-equivalent).

Prior to 2019, HWSM reported projections at the state and national levels; as such state-level population databases were created—which were also aggregated to the national level. Beginning in 2019, population files were constructed for each of the 3,142 counties or county equivalents (e.g., parishes, boroughs, independent cities) in the U.S. The purpose of modeling at the county level is to facilitate evaluation of supply and demand by rurality across states and the nation, and to better model adequacy of health workforce supply for underserved communities and populations. County population files can be combined to produce state population files, which in turn can be summed to produce the national population file.

Construction of the county level population files starts with U.S. Census Bureau data on the aggregate number of people in each county in 2017 by age, sex, and race/ethnicity. The core micro data file on which HWSM's baseline population databases are built is the most recent year of ACS.[a] The ACS provides the demographic and socioeconomic characteristics of a representative sample of the population in each state. Using Census Bureau data on the number of people in each county by age, sex, race, and Hispanic ethnicity, we used random sampling with replacement to draw a sample from the ACS. If the county was primarily non-metropolitan or primarily metropolitan, respectively, we sampled from the non-metropolitan or the metropolitan ACS sample in that county's state. Data from the ACS provides information on medical insurance type, household income, demographics, and whether the person lives in a community or institutional setting.

To add health risk factors and information on disease presence, we combined this initially constructed population file with data from the Behavioral Risk Factor Surveillance System (BRFSS), the Medicare Beneficiary Survey (MCBS), and CMS's Long-Term Care Minimum Data Set (MDS) using random sampling with replacement. The final simulation population database contains profiles for each person that includes: health status variables (e.g., diabetes and

[a] The 2017 ACS file is used to model oral health, updated behavioral health and the general surgeon workforce. The 2016 ACS file was used to model behavioral health demand and allied health occupations. The 2015 ACS file was used to model demand for long term services and support occupations. The 2014 ACS file was used to model demand for nurses. Earlier versions of ACS were used for previous studies of physicians, nurses, and other health occupations.

Exhibit 4: Information in Constructed Population File

Demographics

1. Children (age groups 0-2, 3-5, 6-13, 14-17 years)
   Adults (age groups 18-34, 35-44, 45-64, 65-74, 75+ years)
2. Sex (male, female)
3. Race/ethnicity (non-Hispanic white, non-Hispanic black, non-Hispanic other, Hispanic)

Health-related lifestyle indicators

4. Body weight status (normal, overweight, obese)
5. Current smoker status (yes, no)

Socioeconomic conditions and insurance

6. Household annual income (<$10,000, $10,000 to <$15,000, $15,000 to < $20,000, $20,000 to < $25,000, $25,000 to < $35,000, $35,000 to < $50, 000, $50,000 to < $75,000, $75,000+)
7. Medical insurance status (private, public, self-pay)
8. In managed care plan (yes, no)

Chronic conditions (presence of each condition coded as yes, no)

9. Arthritis, asthma, cardiovascular disease, diabetes, hypertension
10. History of cancer, heart attack or stroke

Geographic location *

11. State, county
12. 2013 NCHS Urban-Rural Classification Scheme for Counties

* In 2019, added county as a dimension and replaced metro/non-metro residency status with the NCHS urban-rural classification.

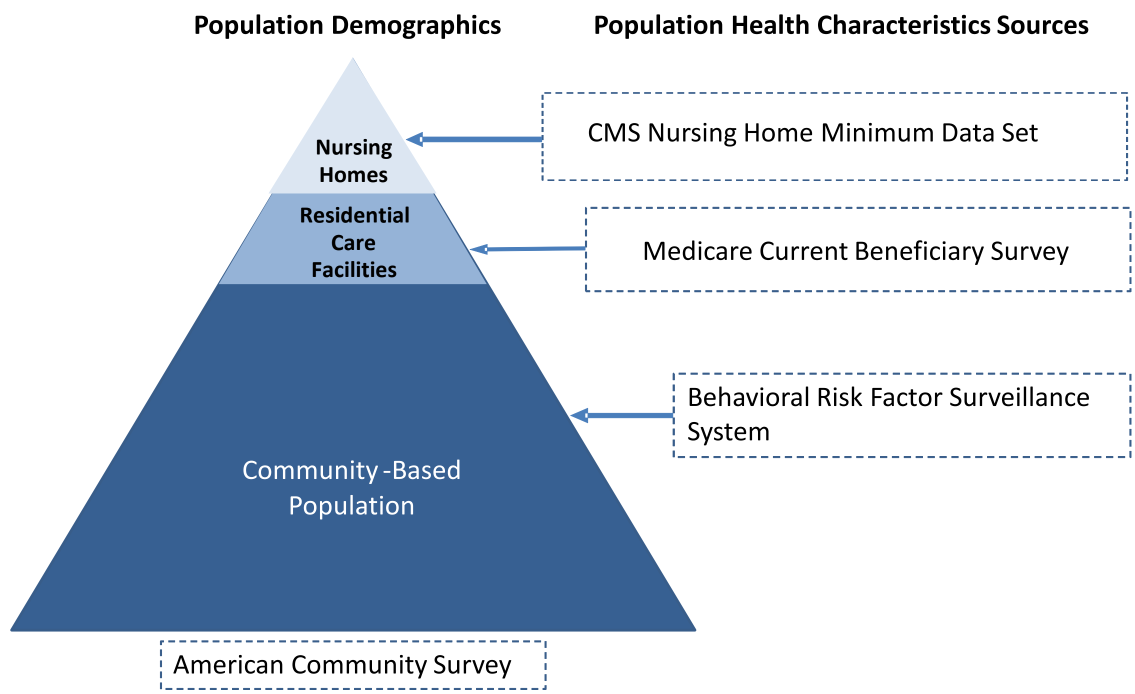
cardiovascular disease), and health-related behavior (e.g., obesity, smoking) in addition to demographic information and socioeconomic characteristics (Exhibit 4).

As illustrated in Exhibit 5, for the non-institutionalized population, each individual in the population file was matched with someone in the BRFSS from the same sex, age group (17 age groups), race, ethnicity, insurance type, household income level (8 income categories), and state of residence.[a] Individuals categorized as residing in a residential care facility or nursing home were randomly matched to a person in the MCBS or Nursing Home MDS, respectively, in the same state, age group, sex, and race and ethnicity strata. The total number of

[a] The first round of BRFSS-ACS matching produced a match in the same strata for 93% of the population. To match the remaining 7%, the eight income levels were collapsed into four (1% matched), then the race/ethnicity dimension was dropped (1% matched), then the same criteria as the first round was applied except State was removed as a stratum (remaining 4% matched), and finally for the fifth round only demographics was included (remaining 0.1% matched).

people living in nursing homes and residential care, by state and age groups, was constructed to match published numbers from CDC.[a] A sample of approximately 1.3 million nursing home residents and 687,000 people living in residential care was merged with the ACS to construct a representative sample of the population residing in nursing homes and residential care facilities.

Exhibit 5: Population Database Mapping Algorithm



[a] National Center for Health Statistics. 2018 National Study of Long-Term Care Providers Web Tables of State Estimates on Residential Care Community Residents. Available at: https://www.cdc.gov/nchs/data/nsltcp/State_estimates_for_NCHS_Data_Brief_299.pdf

About the Behavioral Risk Factor Surveillance System

The BRFSS, administered annually by the CDC, collects data on a sample of over 500,000 individuals. Like the ACS, the BRFSS includes demographics, household income, and medical insurance status on a stratified random sample of households in each state. The BRFSS also collects detailed information on the presence of chronic conditions and other health risk factors (e.g., obesity, smoking). Because BRFSS only reports some variables (e.g., hypertension) biennially, the 2015 and 2017 files were combined to provide records for approximately one million individuals. The 2014 BRFSS was used to model children, as this was the most recent survey where the age of each child is identified.

To create the health risk factor dataset, we gathered health status prevalence percentages for each individual county in the United States (approximate total of 3,142 counties within 50 states and the District of Columbia). The prevalence of 12 health risk factors/conditions in the county-level population data bases are representative of the prevalence of twelve risk factor categories from BRFSS: coronary heart disease, stroke, current smoking, heart attack, current asthma, obesity, diabetes, high blood pressure, arthritis, cancer, high cholesterol, and current insurance status. Smoking, asthma, obesity, and insurance status reflect the individual's current status, while the other 8 categories (coronary heart disease, history of stroke, history of heart attack, diabetes, hypertension, arthritis, cancer, and high cholesterol) reflect lifetime status. Obesity status is calculated based on the individual's current weight.

Developing demand forecasts for future years requires the creation of population databases for future populations as well. This is accomplished by adjusting sample weights of hypothetical people in the baseline population databases such that the weights produce hypothetical populations that mirror Census Bureau projections for future years by demographic groups (age group, sex, race and ethnicity)[11] at the national level, and by population projections estimated by state governments for future-year state and county-level population databases.

Except for the "Population Health" scenario, described later, all the demand scenarios assume that baseline prevalence rates of health and health behavior characteristics remain the same by age, sex, race and ethnicity into the future. A scenario that models achieving select population health goals does model changes in disease prevalence and health risk factors within demographic strata.

Status Quo HWSM demand projections assume:

Prevalence of health behaviors and health conditions within a demographic group are constant across the projection period.

The model's projections account for the health care use and health workforce implications of insurance expansion under the Affordable Care Act (ACA). By 2017, much of the expanded coverage provisions of ACA had been implemented and this is reflected in the baseline demand estimates. The projections for health occupations updated in 2019 do model small increases in medical insurance coverage reflecting ongoing efforts to expand coverage in five states (ID, ME, NE, UT and VA) using published estimates of expanded Medicaid coverage[12], though at the national level the projected expansion is smaller than modeled in previous reports. Thirteen states did not expand Medicaid coverage and have no current plans to do so.

B. Modeling Demand for Health Care Services

This section documents both the development of regression equations employed to estimate health care usage by settings, and the health care usage measures that constitute the dependent variables in the regression equations or the workload measures for care delivery settings like nursing homes and residential care facilities not modeled using regression analysis (Exhibit 6). Exhibit 7 lists the population groups used to estimate the demand for health care services that depend on the population size of potential users.

Exhibit 6: Care Delivery Settings and Health Care Utilization Measures for Healthcare Resources Represented in MEPS

Care Delivery Setting and Service Type	Health Care Utilization Measures
Ambulatory care	
Physician and other provider offices	Total visits, visits by provider type and specialty; Rx scripts
Outpatient departments and clinics [a]	Total visits, visits by provider type and specialty; Rx scripts
Dental offices	Dental non-cleaning visits distributed to general and specialty dentists, dental cleaning visits assigned to dental hygienists
Hospital inpatient and emergency care	
Hospital inpatient (includes skilled nursing facility [SNF] units of hospitals)	Hospitalizations and length of stay overall, and by primary diagnosis (ICD-9); Rx scripts
Hospital emergency department	Emergency visits by primary diagnosis (ICD-9); Rx scripts
Home health and hospice care	
Home Health/Hospice	Total visits by provider type
Post-acute care and Long-term care	
Nursing home (includes free standing SNF)	Total nursing home residents
Residential care facilities	Total population in residential care facilities

Note: [a] Examples of outpatient clinics include well-baby clinics/pediatric outpatient departments; obesity clinics; eye, ear, nose, and throat clinics; family planning clinics; cardiology clinics; internal medicine departments; alcohol and drug abuse clinics; physical therapy clinics; and radiation therapy clinics.

General Approach to Estimating Health Care Utilization

Healthcare seeking behavior was generated from econometrically estimated equations using data from the Medical Expenditure Panel Surveys (MEPS).[a] Five years of data were pooled to provide a sufficient sample size for regression analysis. Regression analyses on baseline data yielded predicted probabilities and intensity of healthcare use by care delivery settings and types of services, based on a person's demographics, income, insurance status, health conditions and risk factors, and rurality of their place of residence. The predicated probabilities are then applied to the relevant population databases for the current year and aggregated by relevant geographic region to produce estimates of market demand for that region in the given year.

To model the impact on health care utilization of expanded medical coverage under ACA, it is assumed that a newly insured person will use health care services at the same rate as a person with private insurance having similar demographic, health status, health risk, and economic characteristics. The Status Quo demand scenario assumes current patterns of care use continue, controlling for changing demographics. Alternative scenarios, described later, make different assumptions regarding care use patterns reflected in emerging care delivery models.

HWSM health care utilization projections assume:

- The current pattern of health care use by demographic and health risk are retained across projection periods.
- Newly insured individuals under ACA will have utilization patterns similar to other insured persons who share the same demographic and health risk characteristics.

Regression coefficients were generated to calculate the estimated annual amount of healthcare utilization by each representative person in the population database attributable to medical office visits, hospital outpatient visits, emergency department visits, hospitalizations, home health visits, and hospice visits as detailed below; and to oral health visits, as detailed in Section IV.1.B.

[a] The 2012-2016 combined MEPS files were used to model demand for oral health providers, updated projections for behavioral health, and general surgeons. HWSM prediction equations are based on combined five years of MEP data, which combined contains data for approximately 170,000 individuals. The 2011-2015 combined MEPS files were used to model demand for behavioral health workers and allied health occupations. The 2010-2014 MEPS files were used to model demand for long term care workers. Earlier years of MEPS data were used to model demand for physicians, nurses, and other health occupations.

Office/clinic visits

MEPS data were used to quantify the relationship between patient characteristics and number of annual office/clinic visits or hospital outpatient department visits with a provider of an occupation or specialty. MEPS contains data on visits to many types of providers, including physicians, psychologists, physician assistants, nurse/nurse practitioners, dentists, optometrists, opticians, physical therapists, and occupational therapists.

Prior to 2019, the prediction equations to model annual visits by provider occupation or specialty were estimated using Poisson regression to reflect the skewed nature of annual visits. In response to inquiries about issues of over dispersion, potential alternative regression models were evaluated, and negative binomial regression was chosen to replace Poisson regression as discussed further in XI.A. The change in regression model had minimal impact on demand projections.

Explanatory variables in the regressions were variables available in both the constructed population file and in MEPS. These variables are age group, race/ethnicity, smoking status, body weight category (normal, overweight, obese), presence of chronic conditions (diagnosed with arthritis, asthma, coronary heart disease, diabetes, or hypertension; history of cancer, heart attack, or stroke), insurance type, enrollment in a managed care plan, household income level, rurality of residence, and MEPS survey year (which is included to test for systematic changes in utilization over the 5-years of MEPS data analyzed).

MEPS reports the highest trained person seen during an ambulatory visit. Consequently, if a patient had a visit to a physician, the MEPS survey did not indicate whether the patient also saw other health professionals during the visit. Predictive equations were developed from the National Ambulatory Medical Care Survey (NAMCS) to determine the likelihood that a patient would see additional health professionals (e.g., registered nurse (RN) or NP, licensed practical/vocational nurse (LPN), or PA) during a clinical visit. In addition, data from NAMCS were used to estimate the number of prescriptions that were generated during an ambulatory care visit, which was then used in the demand projections for pharmacy-related professions.

Hospital-Related Services

Regressions predicting demand for hospital inpatient and emergency services employ the five latest years of MEPS files, along with the latest National Inpatient Sample (NIS) and National Hospital Ambulatory Medical Care Survey (NHAMCS) files.[a] Multiple years of MEPS data were used to increase the size of the sample and provide reliable estimates for hospitalization and

[a] The model currently uses the 2014 NIS and 2014 & 2015 NHAMCS files.

emergency department (ED) visits by medical and surgical conditions. Additional information on the data and methods for modeling demand for hospital inpatient and emergency services are described below.

Hospital Inpatient Services

Utilization patterns of inpatient services by individual characteristics were modeled in three parts:

- The annual probability that an individual would experience at least one hospitalization for each of 28 broad diagnosis categories (with categories defined using ICD-9 and ICD-10 codes).
- The expected length of stay (LOS) for that hospitalization.
- Specialty services and prescriptions received during the hospitalization.

The probability of hospitalization in general, acute care, long term or specialty hospitals for each of the 28 diagnosis categories was modeled with logistic regression using MEPS data. Explanatory variables were the same explanatory variables described previously for modeling office and outpatient visits to providers.

LOS during the hospital was analyzed with Poisson regression using discharge records in NIS. Separate regressions were modeled for each of the 28 diagnosis categories. The dependent variable was total days in the hospital, and the explanatory variables were patient age group, sex, race, ethnicity, insurance type, and presence of diabetes among the diagnosis codes. Because of the large sample size of NIS (over 8 million hospital stays), estimates derived from NIS were stable even for hospitalizations for the condition categories with fewer hospitalizations. Expected LOS calculated from NIS was applied to the individuals in the population database and multiplied by hospitalization probability to estimate each person's expected number of inpatient days during the year for the modeled medical or surgical condition categories.

NIS also was used to determine the expected number of prescriptions that would be filled by hospitalized individuals (which is used to model demand for pharmacists).

Hospital Emergency Department Services

Utilization patterns of emergency department (ED) services were modeled in two parts:

- The probability that a person with given characteristics would have at least one emergency visit during the year for each of 20 categories of services defined by ICD-9 codes.

- During the ED visit, did the patient see a physician, NP, PA and second physician (with the first physician encounter assumed to be an emergency physician and the second physician encounter during the visit assumed to be a specialist consultant). Also modeled was medications prescribed during the visit.

Logistic regression with MEPS data was used to estimate the likelihood that a person with given characteristics would have at least one ED visit during the year for each of the 20 condition categories. MEPS does not identify the medical specialty of providers and lists only the highest level of provider seen. Therefore, the NHAMCS was used to identify the types of services that typically accompany an emergency visit for a particular category of services (namely, medications prescribed and lab tests or exams performed which information is used to model demand for pharmacists and various allied health occupations), and the probability that another provider was seen (e.g., physician, PA, RN/NP or LPN).

Post-Acute Care Services

Demand for post-acute care in hospitals and SNFs that are a part of a hospital are modeled as inpatient services, as described above. Demand for nursing home care in free-standing nursing homes is linked to the size of the population in nursing homes.

Home Health and Hospice Services

The pooled 5-year MEPS files (n~22,000) were used to model home visits. The files contain annual use of home health services, including information on the type of provider during the visit (home health aide, registered nurse, physical therapist, etc.). Prior to 2019, Poisson regression was used to model annual visits by each provider type. Starting in 2019, negative binomial regression was used. The dependent variable was annual visits from a specific provider type. Explanatory variables consisted of the same variables used to model demand for office, outpatient, hospital inpatient, and emergency department care.

Utilization of Healthcare Worker Resources Not Captured in MEPS

Some health workers provide services that are not captured in MEPS or in traditional clinical settings. HWSM models demand for these workers as a provider-to-population ratio (see Exhibit 7). This includes occupations such as nurses, counselors, and physicians who are employed by schools, work in public health departments, or are involved in teaching. Demand is modeled based on the size of the population who might use such services. For example, the demand for school-based services was derived by HWSM directly from the projected size of the population of school-aged children, and under the Status Quo demand scenario if the size of the population of school-aged children increased by 5% then demand for school-based health care would increase by 5%.

Exhibit 7: Care Delivery Settings and Potential Users that Drive Demand for Healthcare Worker Resources Not Captured by MEPS

Care Delivery Setting and Service Type	Workload Measure
Educational institutions	Number of health workers trained annually
Public/community health	Total population
School health	Population aged 5-18 years
All Other	Total population

C. Staffing to Meet Demand for Health Care Services

By applying information on staffing patterns, HWSM converts demand for visits and other utilization measures (described previously) into demand for FTEs by occupation or specialty.

Assuming the base year demand for services in each setting was fully met by the available professionals in that setting, the base year staffing ratio was calculated by dividing the national volume of service used by the number of health care professionals employed in each setting. For occupations that provide services in a single setting, base year utilization was divided by the base year supply to derive the staffing ratio for that occupation. The staffing ratio was then applied to the projected volume of services to obtain the projected demand for providers in every year after the base year. For occupations that provide services across multiple settings (e.g., nurses and therapists), information from the Bureau of Labor Statistics (BLS) on the employment distribution of the care providers in the base year was used to determine the number of individuals working in each setting.

D. Status Quo and Alternative Scenarios

Status Quo Scenario

The status quo demand scenario in HWSM applies current national patterns of care use and delivery to the modeled population and assumes that care use and delivery patterns remain relatively unchanged over time. This scenario models demand considering population demographics, health risk factors, disease prevalence, and economic factors correlated with demand for health care services. This scenario captures population growth and aging over time, as well as geographic variation in demand determinants. When compared against supply projections, this scenario helps inform whether there will be sufficient supply to provide a level of care at least consistent with current levels. The main demand drivers of this scenario are population growth and aging, though the scenario does incorporate small amounts of growth in insurance coverage from a handful of states that have indicated plans to expand Medicaid coverage.

Evolving Care Delivery System Scenario

The evolving care delivery system scenario builds on the status quo scenario, thus considering current patterns of care use and delivery correlated with a person's health and health risk factors, and the impact of changing demographics over time and the associated change in disease prevalence. In this section we discuss the rationale for this scenario and components of this scenario that are modeled for multiple health occupation groups. Components of his scenario that are occupation-specific are described in the respective occupation chapters.

The rationale for this scenario is that the health care system continues to evolve reflecting: (1) innovation and evidence-based medicine; (2) economic considerations, including payment reform and efforts to align patient incentives and health plan incentives; (3) growing use of team-based care with each occupation contributing based on their specialization and evolving scope of practice; and (4) public expectations and policies around population health, care access and quality. This scenario attempts to be forward looking by modeling the health care system the national is striving to achieve and the trends that are moving the health care system in that direction.

This scenario is based on the principles of a high performing health care system striving to (1) achieve population health goals and provide better preventive care, (2) provide a continuum of care across care delivery settings and coordinating multidisciplinary care, (3) identify and manage high risk populations using evidence-based strategies and information technology, (4) improve efficiency of care delivery—including reducing unnecessary or duplicative diagnostics and treatments, and (5) measure and improve quality of care.[13,14] The mechanisms for achieving these principles include policy and payment reform such as value-based insurance design (VBID), risk sharing arrangements such as Accountable Care Organizations (ACOs), patient-centered medical homes (PCMH), team-based care, technological advances, and cost control and other economic considerations. The above principles and mechanisms are inter-related, with some mechanisms helping to accomplish multiple of these principles simultaneously.

A key component of this modeled scenario is **improving population health.** This component builds on the population health scenario modeled previously for HRSA for the allied health workforce (Chapter VII), the long-term services and support workforce (Chapter VIII) and the nursing workforce (Chapter IX), and for IHS Markit's modeling demand for physicians.[15] New policy guidelines, provisions in the ACA, and new reimbursement models are designed to promote preventive care with the potential to improve the health of the entire population (beyond just high risk, high utilization subpopulations). Examples include guidelines and reimbursement for counseling and treatment to promote a healthful diet and physical activity to individuals at high risk for developing cardiovascular disease or diabetes, for smoking cessation, and to improve control of blood pressure, cholesterol levels, and hemoglobin A1c levels.[16–19] The PCMH model is associated with improved adherence to medication for chronic disease—rising from 59% adherence to 64% among PCMH patients compared to a matched control group.[20] Pharmacist-led interventions within the PCMH model have been effective in better controlling glycosylated hemoglobin for patients with diabetes, and improved adherence to medication to control high cholesterol and blood pressure.[21]

The long-term health and mortality implications from achieving population health goals were modeled using a Markov-based microsimulation approach described in detail elsewhere, with the long-term findings then incorporated into HWSM to model the long-term implications for health care use by delivery setting and workforce demand.[22,23] The microsimulation model's prediction equations came from published clinical trials and observational studies, and the simulation was conducted using a nationally representative sample of adults constructed using the National Health and Nutrition Examination Survey (NHANES) combined with Census Bureau population projections. We modeled the potential long-term health impacts and health workforce demand implications of achieving the following population health goals. The modeled assumption is that individuals could reach these goals over a short period of time, though nationally it would take longer to achieve such goals and many people eligible to participate in programs to achieve such goals (such as Medicare's Diabetes Prevention Program) might choose not to participate. Hence, this is a hypothetical scenario modeling if the nation could achieve desired goals rather than an attempt to model a specific set of policies or interventions.

- **Sustained 5% body weight loss for overweight and obese adults**: Numerous lifestyle interventions have achieved 5% or more body weight loss, on average.[24,25] Insurers increasingly are exploring ways to reduce the obesity epidemic in the US with the goal to reduce onset of cardiovascular disease, diabetes, various cancers, and other chronic conditions where obesity is a contributor. One example of an intervention is the new Medicare Diabetes Prevention Program (MDPP) where patients at high risk for developing diabetes can receive counseling designed to improve nutritional intake, increase level of physical activity, and receive other intervention to improve body weight and reduce blood glucose levels. Patients often regain some body weight after an intervention formally ends, but sustained weight loss is possible through a PCMH model or other mechanism that provides long-term counseling and pharmacotherapy.[26,27]

- **Improved blood pressure, cholesterol, and blood glucose levels for adults with elevated levels**: Controlling these key vital signs is part of disease management programs for cardiovascular disease, diabetes, and other chronic diseases. In addition, improving these vital signs is part of the nation's population health goals, as illustrated by the Healthy People goals.[28,29] These goals can be achieved with appropriate screening, lifestyle counseling to improve nutritional intake and increase physical activity, pharmacotherapy, and other interventions or policies (e.g., VBID) to improve adherence to medications. Clinical trials indicate that patients with hypercholesterolemia can reduce total blood cholesterol by 34.42 mg/dL (CI, 22.04-46.40) by using statins[30]; patients with uncontrolled hypertension can reduce systolic blood pressure by 14.5 mm Hg (CI, 14.2-14.8) and diastolic blood pressure by 10.7 mm Hg (CI, 10.5-10.8) by using anti-hypertensives[31]; and patients with elevated hemoglobin A1c levels can reduce A1c by 1 percentage point (CI, 0.5-1.25) annually—with modeled improvements occurring gradually until diabetes control is reached at A1c of 7.5%.[32] We modeled the above reduction in blood pressure, cholesterol levels, and blood glucose levels for people with elevated levels.
- **Smoking cessation**: Smoking cessation is a key component of disease management programs, preventive care, and the nation's population health strategy. Patients who stop smoking can lower their risk for various cancers, diabetes, cardiovascular disease and other diseases.[33] We model that 25% of smokers quit smoking, though our modeling work reflects high levels of recidivism.

Model findings indicate that achieving these population health outcomes results in a healthier population which requires slightly less per capita use of many types of health care services over time. However, achieving these outcomes reduces mortality which increases future demand for health care services to support a larger and older population from delayed mortality.

In addition to modeled long term clinical outcomes with implications for health workforce demand, population health strategies can have short term implications by changing care use patterns. One study reports that a population health strategy implemented among a population that was predominantly uninsured, minority, and lower income reduced ED visits by 21.4% and reduced inpatient care by 36.7% over the subsequent 12 months.[34] Other aspects of evolving care delivery are described in later chapters discussing specific health occupations and care delivery settings.

IV. Oral Health Care Provider Model Components (updated 2019)

This chapter contains a description of the data, assumptions, and methods used to adapt HWSM to model the supply of and demand for general and specialty dentists and dental hygienists. Projections for these oral health occupations were developed by county and aggregated to produce urban/suburban/rural estimates at the state and national levels.

The research team reached out to professional associations representing oral health professions to identify the best available data sources, discuss trends affecting workforce supply and demand, and to provide the opportunity for feedback on preliminary findings. The information provided in this technical documentation and in HRSA reports does not necessarily reflect the views of the associations that responded to our invitation to participate in the workforce study and there may not be clear consensus on all assumptions. Individuals from the following professional associations participated:

- American Dental Association (ADA)
- American Dental Assistant Association (ADAA)
- American Dental Education Association (ADEA)
- American Dental Hygiene Association (ADHA)
- Dental Assisting National Board (DANB)

Many of these professional associations provided information on the current supply of professionals as well as the number and characteristics of new graduates. In the remainder of this chapter we expand on how HWSM was adapted to model supply and demand for oral health providers.

A. Modeling Supply

Sufficient data were available to project future supply of dentists and dental hygienists, but not dental assistants. Several supply scenarios were modeled. The status quo scenario, which assumes that current supply patterns for oral health professionals remain the same throughout the forecast, extrapolates current trends in supply determinants: number and characteristics of current and new providers, hours worked patterns, and attrition patterns. Alternative scenarios modeled the sensitivity of future supply to changes in key trends and assumptions—including (a) ±10% change in annual numbers of new graduates entering the workforce, and (b) ±2-year change in observed retirement patterns.

Estimating the Base Year Workforce Supply

HWSM supply projections are built on baseline numbers and characteristics of each provider type. For dentists, these data come from the American Dental Association's (ADA) 2017 Master File, which contains demographic information on every individual who completed dental school and categorizes dentists into seven groups based on specialty: general dentists, orthodontists, pediatric dentists, oral surgeons, periodontists, endodontists, and all other dentists (Prosthodontists are the largest component of the "other dentists"). Dentists in the 2017 ADA Master File who were unlicensed and not retired were treated as inactive.

Base year demographic information for dental hygienists comes from the ACS. ACS data files for 2013 through 2017 were combined to ensure a sufficient sample size in each state to use sampling with replacement to create a representative population of the national dental hygienist workforce. The size of the sample drawn reflected the state-level estimates of active providers from the 2017 OES. However, the number sampled was scaled to match the national total in the ACS, as the OES may count dental hygienists with multiple positions multiple times and could therefore produce national estimate that are too large. The individual records that contained information on age, sex, and state of residence from the ACS and the ADA were retained as the base year supply of active hygienists and dentists, respectively.

Modeling New Entrants

The number of new dentists entering the workforce each year of the projection period (2018-2030) is based on the latest available survey data from the ADA,[40] which reported sex, race/ethnicity, and state of residence for the 6,238 dentists graduating in 2018 as well as in which of the six NCHS urban-rural classifications the new dentists are working. We apply these distributions to simulate the demographic distribution and geographic location of new dentists graduating in future years. The number of graduates in each dental specialty were subtracted from total graduates to estimate the number of new general dentists. A breakdown of these graduates by specialty, sex, race/ethnicity, and age is shown in Exhibit 8. The age distributions were created by calculating the age at graduation (or completion of advanced education) for all dentists in the ADA Masterfile who graduated since 2010. The 2018 Survey of Allied Dental Education reported the age, sex, race/ethnicity, and state of residence of that year's 7,385 new dental hygienists.[40]

Profiles of individual new dentists and dental hygienists entering the workforce each year of the projection period (microdata) were simulated using these state, age, race, and sex distributions.

HWSM oral health workforce supply projections assume that the annual number of graduates entering the workforce, as well as the age and sex distribution of new oral health professionals remain the same in the future (e.g. 49% of new dentists and 96% of new dental hygienists are female each projection year).

Exhibit 8: Annual Graduates, by Occupation/Specialty, Sex, Race/Ethnicity, and Age

Occupation	Annual Graduates	Female (%)	Race/Ethnicity (%)				Age Distribution (%)			
			White	Black	Other	Hispanic	*≤25*	*26-30*	*31-40*	*≥41*
General Dentists	4,580	49	57	5	29	9	3	72	23	2
Orthodontists	372	43	44	8	35	13	0	65	34	1
Pediatric Dentists	438	64	53	8	28	11	1	59	39	1
Oral Surgeons	262	15	69	3	23	5	1	31	67	1
Periodontists	172	42	62	<1	27	11	1	49	48	2
Endodontists	211	34	68	5	23	4	0	50	47	3
Other Dentists	203	37	61	1	27	11	1	40	56	3
Dental Hygienists	7,385	96	71	4	11	14	47	34	16	3

Sources: 2017-2018 Survey of Dental Education and 2017-2018 Survey of Advanced Dental Education for estimated number of dentists, race, and percent female; 2017 ADA Master File for age distribution of dentists; 2017-2018 Survey of Allied Dental Education for dental hygienists' number and characteristics.

Modeling Workforce Participation

Labor force participation rates for oral health professionals age 50 or less by age, sex, race/ethnicity, and occupation were estimated based on 2013-2017 ACS data regarding employment status (active/inactive). Because dental specialties are not recorded in the ACS, all dentists are assumed to have the same workforce participation probabilities, but dental hygienists have different probabilities.

The estimated probabilities that a dentist retires each year in the supply projections were calculated by age and dental specialty using age of retirement for all dentists who retired between 2010 and 2017 as recorded in the 2017 ADA Masterfile. Because dentists' retirement patterns are divided into seven groups based on dental specialty, we did not also separate them into demographic groups due to sample size concerns. Dental hygienists' probabilities of attrition by age were calculated from the 2013-2017 ACS data. Age cohort differences across years were used to estimate the net number of people leaving the workforce each year. For example, one estimate of net attrition between age 65 and 66 is calculated by comparing active supply of providers age 65 in 2015 versus active supply of providers age 66 in 2016. To increase the amount of data on which estimates were based, age-specific retirement estimates were averaged across the 2013-2017 period. Sample size was insufficient to model dental hygienist attrition by sex or by race/ethnicity.

Modeling Hours Worked

Ordinary Least Squares (OLS) estimates of hours worked for each oral health occupation were generated from the latest 5 years (2013-2017) of ACS data. The dependent variable was total hours worked in the previous week; explanatory variables consisted of age group, sex, race, and a calendar year indicator (Exhibit 9). Because the ACS does not include information on dentist specialty, the same hours worked regression coefficients are used for all specialties.

Oral health professionals in the projections have a calculated number of hours worked per week created based on the OLS regression results. These average hours worked per week differ by age, sex, race, and occupation. As a dentist's or dental hygienist's age increases during the projection years, hours worked for that provider can change accordingly. While dentist hours worked data is not available by dental specialty, survey data from the ADA suggests that specialty dentists as a group work a similar number of hours as general dentists.[41]

The expected number of hours worked by each individual was converted to FTE supply by dividing the total person- hours worked by 40. This creates a uniform standard of 1 FTE as working 40 hours per week regardless of the occupation; as a result, the initial FTEs of an occupation can differ from the actual count of persons employed in the occupation.

Exhibit 9: OLS Regression of Dentist and Dental Hygienist Weekly Hours Worked

Parameter	Dentists	Dental Hygienists
Intercept	42.35	38.09
Age 35 to 44	-1.88	-1.37
Age 45 to 54	-1.55	-1.55
Age 55 to 59	-2.18	-2.35
Age 60 to 64	-4.46	-2.88
Age 65 to 69	-8.05	-5.56
Age 70+	-11.24	-10.21
Hispanic	1.10	0.72
Non-Hispanic Black	1.50	4.76
Non-Hispanic Other	0.73	0.82
Female	-4.17	-6.00

Note: Comparison groups are: age <35, male, Non-Hispanic White

Modeling State-Level Supply and Migration

HWSM accounts for annual movement of oral health professionals across states. This is accomplished in two steps. First, logistic regression on ACS data is used to estimate the probability of migrating to any other state for the under 50 population as a function of age group, sex, race, the state's population, and a year indicator. Comparing each person's move probability with a random number between 0 and 1 determines which providers move each year. The likelihood that each person moving will relocate to a specific state is based on the proportion of people moving to that state as observed in ACS data. For example, if ACS shows 10% of dentists who relocate moving to California, then in HWSM each dentist who moves has a 10% probability of moving to California. When an oral health provider moves to a specific state, HWSM then tags that provider by the level of rurality of the area in which s/he practices. The provider's rurality designation is based on the current rurality distribution of the workforce in the state. For example, if in a state 50% of dentists work in a large core metro location as determined by the current rurality distribution in each state from the 2017 ADA Masterfile, then each dentist moving to that state has a 50% probability of being assigned a designation as working in a large core metro area.

B. Modeling Demand

Modeling Annual Visits to an Oral Health Provider

Prediction equations in HWSM model annual visits to dental hygienists, and annual visits to each type of dentist: general or pediatric dentist, endodontist, oral surgeon, orthodontist, periodontist, and other type of dentist. These prediction equations were estimated using negative binomial regression with the MEPS Dental Visit Files from 2012-2016. Separate regressions were estimated for children and adults, and separate regressions were estimated for dental hygienists and for each dentist specialty.

MEPS does not have pediatric dentists as a unique specialty, so when children visited a dentist MEPS does not indicate whether services were provided by a pediatric dentist or by a general dentist. Information provided by ADA, based on ADA's survey of dental practices, indicates that about 46% of dental visits by children under 2 years of age were for care provided by a pediatric dentist with the remaining 54% of visits to a general dentist. For children ages 2 to 4 approximately 40% of dental services were provided by a pediatric dentist. This percentage falls to 23% for children and adolescents ages 13 to 17. In total, approximately 26% of dental visits by children and adolescents were to a pediatric dentist and 74% were to a general dentist. In HWSM, we use these percentages to model the proportion of dental visits by children and adolescents that likely receive care from general dentists and from pediatric dentists.

The regressions model the correlation between people's characteristics and annual use of oral health services. The dependent variable in each regression was annual visits to the oral health provider type. Explanatory variables were the same demographic, economic, health status, and health behavior variables described in Chapter III for modeling demand for ambulatory care visits. Coefficients from these regressions were applied to the population file to produce estimates of the expected number of oral health visits to each provider type for the population in each county.

Data limitations precluded the inclusion of dental insurance as a predictor of the demand for dental care services. Although dental insurance is available in MEPS, this information is unavailable in the files used to construct the population database. Therefore, in the MEPS-based regressions the influence of dental insurance on use of oral health services is reflected in the regression intercept and other explanatory variables such as presence of medical insurance (which is likely positively correlated with having dental insurance). In comprehensive testing, predictions of oral health care utilization among the population generally were not improved by using dental insurance coverage as a predictor in lieu of medical insurance coverage.

Modeling Oral Health Provider Staffing

The simulated demand for dental services was translated to demand for providers through the national provider-to-visit ratios. Because dental services are delivered mainly in a clinic setting[45], staffing ratios in other settings (e.g., emergency departments) were not developed. To determining provider-to-visit ratios, HWSM projections assume that the demand for oral health services (aggregated for the nation) in the base year was met exactly by the base year supply of providers (see Exhibit 10).

The status quo demand projections hold provider-to-visits staffing ratios unchanged during the projection period and estimates of demand for oral health service delivery in each county and state models the level of care if people in that county or state had access to and used oral health services at the national rate for a population with similar characteristics and socioeconomic status. That is, national ratios (by specialty) of dentists-to-dental visits (excluding teeth cleaning) in the base year are applied to the projected visits in future (projection) years to determine demand projections for dentists; the ratio of dental hygienists-to-teeth cleaning visits are applied to projected tooth cleaning visits to determine the future demand for dental hygienists.

Exhibit 10: Summary of Dentist and Dental Hygienist Workload Drivers: 2017

Provider Type	Estimated Providers[a]	Estimated Visits[b]	Provider to Visit Ratio
General Dentists	151,180	88,344,000 visits by adults; 10,140,000 visits by children & adolescents	1:651
Pediatric Dentists	7,330	Of 13,703,000 dental visits by children, of which 3,563,000 (26%)[c] to a pediatric dentist	1:486
Endodontists	5,380	1,570,000	1:292
Oral Surgeons	7,060	6,568,000	1:930
Orthodontists	9,970	28,469,000	1:2,885
Periodontists	5,470	2,969,000	1:543
Other Dentists	4,080	1,656,000	1:406
Dental hygienists	147,470	285,200,000[d]	1:1,935

Notes: [a] Sources: 2017 American Dental Association Masterfile for dentists, and 2013-2017 American Community Survey for dental hygienists. [b] Source: Analysis of the 2012-2016 Medical Expenditure Panel Survey applied to 2017 population. [c] Source: Surdu et al, 2019[46] [d] Total visits for dental cleaning

V. Behavioral Health Care Provider Model Components (updated 2019)

Behavioral health care is an umbrella term for care that addresses any behavioral problem, including mental health and substance abuse conditions, stress-linked physical symptoms, patient activation and health behaviors. In its 2016 and 2018 reports, HRSA reported workforce supply and demand projections for psychiatrists, psychologists, psychiatric/mental health nurse practitioners (NPs), psychiatric/mental health physician assistants (PAs), substance abuse and behavioral disorder counselors (addiction counselors), mental health counselors, school counselors, social workers, marriage and family therapists (MFTs), and psychiatric aides & technicians.[53,54] These occupations are included in HRSA's updated report, and although the name for some occupations has been changed in this report the definition for each occupation is the same as in previous reports with the exception of psychologists and social workers.

The 2016 report[54] included all psychologists trained at the master's degree or higher, whereas HRSA's 2018 report includes doctorate-level psychologists only. Due to data challenges distinguishing between clinical social workers and social workers in non-clinical roles, the criteria used to identify social workers for modeling have evolved across studies. In the 2018 report, the model includes social workers trained at the master's degree or higher. However, the model did not distinguish between clinical and non-clinical social works given the constraint of national data sources such as ACS, which do not allow one to identify which social workers are clinical social workers. The 2018 report[53] explored emerging titles in the behavioral health workforce—peer specialists, psychiatric pharmacists, licensed behavioral analysts and certified behavior analyst assistants/associates—though currently there is insufficient data to model supply and demand for these occupations.

For the 2018 report and 2019 update, the research team reached out to professional associations representing behavioral health professions to identify the best available data sources, discuss trends affecting workforce supply and demand, and to provide the opportunity for feedback on preliminary findings. The information provided in this technical documentation and in HRSA reports does not necessarily reflect the views of the associations that responded to our invitation to participate in the workforce study and there may not be clear consensus on all assumptions. Individuals from the following professional associations participated:

- Association of Social Work Boards (ASWB)
- American Academy of Physician Assistants (AAPA)
- American Association for Marriage and Family Therapy (AAMFT)
- American Psychiatric Association (APA)
- American Psychiatric Nurses Association (APNA)
- American Psychological Association (APA)[a]
- American School Counselor Association (ASCA)
- Association for Addiction Professionals (NAADAC)
- College of Psychiatric and Neurologic Pharmacists (CPNP)
- Council on Social Work Education (CSWE)
- National Board for Certified Counselors (NBCC)

Many of these professional associations provided data on current supply and the number and characteristics of new graduates. The remainder of this chapter describes how HWSM was adapted to model supply and demand for behavioral health providers.

A. Modeling Supply

For the occupations for which sufficient data exists to project future supply, multiple scenarios are modeled. A status quo scenario extrapolates current trends in supply determinants: number

[a] The American Psychological Association (APA) recently completed a workforce study using HWSM. The data, methods, assumptions and findings in the HRSA study are consistent with those in the APA. The projections differ slightly, though, because HRSA uses a FTE definition of 40 hours worked per week, whereas the APA projections are based on the average hours worked by psychologists (39.0 hours/week).

and characteristics of current and new providers, hours worked patterns, and attrition patterns. Alternative scenarios modeled the sensitivity of future supply to changes in key trends and assumptions—including (a) ±10% change in annual numbers of new graduates entering the workforce, and (b) if retirement patterns were to change such that providers retired up to two years earlier or delayed retirement by up to two years, on average, relative to historical retirement patterns.

Estimating the Base Year Workforce Supply

The data sources for estimating starting supply in 2017, by state, were the following:

- Psychiatrists: American Medical Association (AMA) Master File
- Psychiatric/mental health physician assistants: National Commission on Certification of Physician Assistants (NCCPA) Statistical Profile of Certified Physician Assistants[55]
- Psychiatric/mental health NPs: American Association of Nurse Practitioners (AANP) NP fact sheet[56]
- Psychologists: American Psychological Association for the de-duplicated state totals of licensed psychologists
- Addiction counselors, social workers and psychiatric technicians and aides: Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES)
- Mental health counselors: National Board for Certified Counselors (NBCC) for the de-duplicated state totals of licensed mental health counselors
- School counselors: Department of Education National Center for Education Statistics (NCES)
- Marriage and family therapists: Substance Abuse and Mental Health Services Administration's (SAMHSA) Behavioral Health, United States (2012) report, with total de-duplicated marriage and family therapist licenses by state—using 2011 data and HWSM to simulate supply to a starting level in 2017

The AMA data contains information on psychiatrists' age and sex, but the above other data sources indicating total number of licensed or active providers by state do not contain provider characteristics. To fill in this gap, 2013-2017 ACS data, which contain demographic information for each occupation (including age, sex, and race/ethnicity) were used. Multiple years of ACS data were combined to ensure a sufficient sample size in each state to draw a representative sample (with replacement) of the workforce population by demographic. The size of the sample drawn is equal to the state-level estimates of licensed or active providers from the above data sources. For occupations with *licensed provider* counts a random sample was drawn from all such providers (active and non-active) in the ACS. For occupations with *active provider* counts a random sample of active providers was drawn from ACS. For purposes of the ACS draw, active status is based on an employment status variable, with responses of "not in the labor force" considered inactive.

For psychiatric NPs and PAs, a sample was drawn from the overall NP and PA populations, as ACS does not specify specialty area. This makes the implicit assumption that psychiatric NPs and PAs have similar demographics to all NPs and all PAs, respectively, within each state. For social workers, the sample was drawn from the population of social workers in ACS with education level of master's degree or higher. For addiction counselors and mental health counselors the sample was drawn from the ACS general occupation of counselors (as ACS does not identify counselors by area of specialization). The mental health counselor sample was drawn from the population of counselors in ACS with education level of master's degree or higher, while the sample of addiction counselors was drawn from the population of counselors with education level of associate degree or higher. For school counselors, the sample was drawn from the population of secondary school teachers in ACS—reflecting feedback from American School Counselor Association (ASCA) that the demographics of teachers likely better represents the demographics of school counselors than the demographics of the broad counselor occupation category in ACS.

As discussed in detail in Chapter II, HWSM uses a microsimulation modeling approach that simulates labor force participation decisions at the individual provider level. For modeling, using the above data sources, a database was created containing a simulated population of the behavioral health workforce in each state with each individual record containing occupation, state, age, sex, and race/ethnicity. HWSM uses this database as the starting point to project future supply through 2030.

Modeling New Entrants

To model additions to the workforce each year, a synthetic population was created wherein the number of newly created individuals for the simulation analysis reflects annual new graduates and the demographics of these new graduates (Exhibit 11).

The number of psychiatrists completing their residency training in 2017-2018 is 1,187 (which consists of 1,151 psychiatrists completing residency from an Accreditation Council for Graduate Medical Education program and 36 from American Osteopathic Association accredited programs – including 390 physicians completing training in child and adolescent psychiatry.)[57] The AMA Masterfile contains the year each psychiatrist completed his or her graduate medical education;

the age and sex distribution of new graduates between 2010 and2017 were used to calculate the age and sex distribution of new psychiatrists. For psychiatric nurse practitioners and physician assistants, the annual number of new graduates was estimated using data from the American Association of Colleges of Nursing for nurse practitioners and the Physician Assistant Education Association for physician assistants. The sex and race distribution of psychiatric nurse practitioners and physician assistants also came from annual reports released by these two associations.[55]

For occupations other than the psychiatrists, psychiatric nurse practitioners and psychiatric physician assistants, the 2017 Integrated Postsecondary Education Data System (IPEDS) data was used to determine the number of annual new graduates as well as the sex and race distribution of the new graduates, as IPEDS collects the number of new graduates by sex and race for each Classification of Instructional Programs (CIP) code and degree level. Only master's degrees for the most appropriate CIP code were counted in this analysis, except for addiction counselors, which included associates, bachelor's and master's degrees.

The ACS file contains information on the workforce from the previous year plus any additions or subtractions to the workforce. To calculate the age distribution of new entrants to the workforce for the non-physician occupations, the number of providers of a particular age (e.g., age 29) in 2013-2016 ACS data were compared to the number of such providers in the subsequent year ACS annual file who were one year older (e.g., age 30). The amount by which the number of providers age 30 in 2016 exceeds the number of providers age 29 in 2015 reflects the net number of new providers entering the workforce at age 29-30. With this information, the approximate age distribution of new entrants to the workforce is estimated. Multiple years of data were used to increase sample size by individual age and occupation. The state distributions of providers aged 30-39 years were used to assign future new entrants in the model to a state.

Exhibit 11: Age, Race, and Sex Distribution of Entering Behavioral Health Professionals

<table>
<tr><th rowspan="2">Occupation</th><th rowspan="2">Annual Graduates</th><th rowspan="2">Female (%)</th><th colspan="4">Race/Ethnicity (%)</th><th colspan="4">Age Distribution (%)</th></tr>
<tr><th>White</th><th>Black</th><th>Other</th><th>Hispanic</th><th>≤25</th><th>26-30</th><th>31-40</th><th>≥41</th></tr>
<tr><td>Psychiatrist</td><td>1,187</td><td>56</td><td>-</td><td>-</td><td>-</td><td>-</td><td>0</td><td>11</td><td>73</td><td>16</td></tr>
<tr><td>Psychologist</td><td>3,795</td><td>75</td><td>69</td><td>10</td><td>9</td><td>12</td><td>3</td><td>41</td><td>35</td><td>21</td></tr>
<tr><td>Mental health counselor</td><td>5,751</td><td>83</td><td>62</td><td>21</td><td>5</td><td>12</td><td rowspan="3">4</td><td rowspan="3">42</td><td rowspan="3">32</td><td rowspan="3">22</td></tr>
<tr><td>Marriage and family therapy/counselor</td><td>3,102</td><td>84</td><td>56</td><td>15</td><td>10</td><td>19</td></tr>
<tr><td>Substance abuse/addiction counselor</td><td>2,613</td><td>72</td><td>58</td><td>24</td><td>7</td><td>11</td></tr>
<tr><td>School counselor</td><td>11,414</td><td>83</td><td>63</td><td>14</td><td>6</td><td>17</td><td>48</td><td>46</td><td>0</td><td>6</td></tr>
<tr><td>Social worker</td><td>28,192</td><td>86</td><td>58</td><td>19</td><td>7</td><td>16</td><td>7</td><td>68</td><td>9</td><td>16</td></tr>
</table>

Sources: Annual graduates from the 2017 IPEDS, except for psychiatrist graduate data from AMA. Demographics are based on analysis of ACS, except for psychiatrist characteristics derived from AMA data. Race is not available for psychiatrists.

Modeling Workforce Participation

For all occupations except psychiatry, labor force participation rates were calculated for providers age 50 or less by age, sex, race/ethnicity, and occupation as 1 minus the proportion of such individual providers in the 2013-2017 ACS data who were classified as "not in the labor force." Data for modeling starting supply of psychiatrists, as with other physician specialties modeled by HRSA, comes from the American Medical Association (AMA) Masterfile. While this data contains little information with which to model labor force participation patterns for physicians, published studies suggest few earlier retirements, with physicians commonly retiring between age 60 and 69.[58] Possible reasons why there are few early retirements from active practice include high debt load from their training, higher earnings potential, and the need to maintain proficiency level and continuing medical education to remain licensed. We model all physicians under age 50 as active.

Attrition patterns for each profession (except psychiatrists) were based on 2013-2017 ACS data for the same occupation categories as used to estimate labor force participation rates for the under-50 occupation. Labor force attrition probabilities were constructed based on comparing whether an individual is employed in a given year and the subsequent year. Cohort differences across subsequent years of data were used to estimate the net number of people leaving the workforce each year. For example, net attrition between age 65 and 66 was estimated by comparing active supply of providers age 65 in a given year to active supply of such providers age 66 the subsequent year. Multiple years of data were used, to increase sample size. The attrition probabilities vary by occupation and age, but sample size was insufficient to model attrition by sex or race/ethnicity.

Attrition patterns for psychiatrists came from analysis of Florida's 2012-2013 Physician Survey, where physicians were asked about their intention to retire over the upcoming three years. Rates differ by age and sex—although attrition rates for men and women were similar.

Modeling Hours Worked

Ordinary Least Squares regression was used to model hours worked patterns using a separate regression for each health occupation. For psychiatrists, physician survey data across four states (FL, SC, NY, MD) covering the period 2012-2018 was used. The dependent variable was hours worked per week in patient care activities. Explanatory variables consisted of dichotomous[a]

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[a] These specialty variables take on the value of 1 if the person is in that specialty, and 0 otherwise.

variables for each medical specialty (including a variable for psychiatry), 5-year age groups, sex, and interaction terms between age and sex. The state survey data identifies physician specialty, whereas ACS, which also contains hours worked data, identifies physicians but not their specialty.

A similar OLS regression approach was employed with ACS data to separately model hours worked patterns for the other health occupations, but with a different model specification. The dependent variable was total hours worked in the previous week. Explanatory variables consisted of age group, sex, race, and a year indicator (as the ACS pooled data from 2013-2017).

Estimates and projections take into consideration the changing demographics of the workforce and that average hours worked per week differ by age, sex, race, and occupation. Then, the expected number of hours worked by each individual was converted to FTE supply by dividing the total person- hours worked by 40. This creates a uniform standard of 1 FTE as working 40 hours per week regardless of the occupation but also means that the initial FTE of an occupation can differ from the actual count of persons employed in the occupation.

Modeling State-Level Supply and Migration

Behavioral health occupations often have different levels of surplus and shortage in different parts of the United States. To better estimate this, HWSM includes state-level supply estimates where sufficient data is available. In the ACS and OES, some occupations do not have totals reported in every U.S. state, so state-level supply estimates are unavailable for these occupations. Furthermore, state-level estimates are unavailable for some behavioral health specialties or occupations (including marriage and family therapists, behavioral health PAs, and behavioral health NPs).

For occupations with sufficient state-level data, HWSM models future movement of behavioral health professionals across states. This is accomplished in two steps. First, a logistic regression on ACS data estimates the probability of migrating to any other state for the workers under age 50 as a function of age group, sex, race, the state's population, and a year indicator. Then, the simulation randomly assigns each individual a probability of moving based on their demographic characteristics and assigns a new state to those who move based on the state distribution of observed graduates. ACS data cannot be used to model psychiatrist cross-state mobility because ACS does not identify physician specialty; however, each new physiatrist is assigned to a state using the state distribution of psychiatrists who recently completed residency using AMA Masterfile data.

B. Modeling Demand

Chapter III provides an overview of the data sources and approach to model demand for health care services and providers. This section provides additional detail of analyses specific to modeling demand for behavioral health providers.

Demand Scenarios

Demand for behavioral health providers traditionally has been modeled under two scenarios. The status quo scenario models future demand under current care use and delivery patterns, accounting for changing demographics and variation across individuals in patterns of seeking behavioral health services. This scenario sets national demand equal to supply in 2017 to enable extrapolating a "2017 level of care" to future populations. The exception is that for psychiatrists demand starts 5,906 FTEs higher than supply to reflect the number of providers required to remove all mental health professional shortage area (HPSA) designations.[3] (The estimate for 2019 now exceeds 6,100). This scenario is used to assess whether the nation's future behavioral health workforce will be sufficient to provide at least the current level of care, even though many may consider current levels inadequate given reports of unmet need.[59]

Past behavioral health reports have modeled an unmet needs scenario, which reflects the additional providers required to address both demand and unmet need.[53,54] The rationale for modeling this unmet need scenario was that the health system continues to evolve to improve access to and comprehensiveness of behavioral health services. These trends include: better affordability through increased coverage by insurance; more intensive use of screening; efforts to decrease stigma; better understanding of how to address behavioral health issues; increased integration of primary care and behavioral health; greater use of team-based care with a broader range of behavioral health providers that provides opportunities for task shifting and providing a more comprehensive range of behavioral health services; and greater use of technology such as telemedicine to reduce barriers to accessing care in rural areas and improve care to patients with mental health needs in emergency departments, nursing facilities, and other care settings.

Historically the unmet needs gap was modeled at 20%, reflecting a likely lower bound on the true level of unmet need. In 2016 and 2017, respectively, 18.1%[60] and 18.9%[61] of adults in the U.S. indicated having any mental illness (AMI), defined as "having a diagnosable mental, behavioral, or emotional disorder, other than a developmental or substance use disorder assessed by the Mental Health Surveillance Study (MHSS)." Among adults in 2016 and 2017, respectively, 14.4% and 14.8% reported receiving mental health services in the past year—defined as "having received inpatient treatment/counseling or outpatient treatment/counseling or having used prescription medication for problems with emotions, nerves, or mental health."[61] Comparison of these estimates would suggest that only 78-80% of adults needing some level of mental health services received any services during the previous year, but adults receiving services includes people without any indication of mental illness. Survey results suggest that 27% of adults with AMI did not receive mental health services during the previous year—though giving us an estimate of between 20-27% of which we used the more conservative 20% estimate.

However, there are several issues with the 20% unmet needs estimate. One, this estimate was calculated based on adult patient self-report of having received any services—though adults with AMI who receive no services likely have lower mental health needs, on average, as compared to adults who receive services and adults with AMI who received services may still have unmet need.[62,63] Two, children and adolescents possibly have higher rates of unmet need than do adults, but MHSS does not collect sufficient information to quantify unmet need for mental health services for children and adolescents. Three, the unmet needs estimate for addiction counselors is likely different than the unmet needs estimate for mental health and even within the behavioral health workforce the level of unmet need likely varies by occupation. Consequently, for this updated study we only include projections using the "status quo" methodology.

Addressing Data Limitations

Adaptation of HWSM to model demand for behavioral health services and providers required addressing critiques of HWSM and data limitations.

One critique of the prediction equations used in HWSM has been the lack of variables related to mental health or substance abuse. While not directly measuring mental health, many of the patient characteristics included in HWSM are correlated with receipt of mental health services — including demographics, family income level, presence of chronic disease, insurance type (especially insured by Medicaid), lifestyle, and metro/non-metropolitan location. However, HWSM contains no information on use of illicit drugs, alcohol consumption, and mental health variables such as presence or severity of depression. This omission reflects data challenges and the need for variables with the same definitions in both (a) MEPS and data sources used to estimate the relationship between patient characteristics and use of health care services, and (b) the population file to which the prediction equations are applied.

MEPS contains information on patients' visits to psychiatrists, psychologists, and social workers. As discussed in Chapter III, for modeling ambulatory (office and outpatient) visits Poisson regressions are estimated, where number of annual visits to a specific type of provider is the dependent variable and the explanatory variables consist of demographics, lifestyle variables, family income, insurance information, presence of select chronic conditions, and indicator of residing in a metropolitan area. However, MEPS does not specifically identify visits to mental health counselors, marriage family therapists, and addiction counselors because these occupations are not differentiated in MEPS (but rather are listed under the "all other non-physician" category). Similarly, while MEPS identifies visits to NPs and PAs it does not specifically identify visits to psychiatric NPs and PAs. Associated with each visit is a reason code which can indicate whether the primary reason for the visit was associated with mental health. The sample size for mental health visits to NPs and PAs is too small to provide reliable regression results. Therefore, to construct prediction equations for patients' annual use of ambulatory services for these occupations we did the following:

- **Mental health counselors, marriage family therapists, and addiction counselors**: Total annual ambulatory behavioral health visits were used to develop the prediction equations describing the relationship between patient characteristics and use of mental health services. The analysis included visits to psychiatrists, psychologists, social workers, and the "all other non-physician" category where the visit was indicated as a visit for mental health or substance abuse. Using this broad category of behavioral health visits relies on the assumption that patient characteristics correlated with greater number of mental health visits to psychiatrists, psychologists, clinical social workers or other non-physicians is also correlated with greater use of services provided by mental health counselors, marriage family therapists, and addiction counselors. (As discussed later, further adjustments were made to model demand for addiction counselors). Using projected total behavioral health visits as the workload driver will overstate the actual number of visits to individual provider occupations but serves as a scalar for the projected growth rate in demand and a scalar for how demand varies across different geographic areas.
- **Psychiatric NPs and PAs**: Due to insufficient sample size in MEPS, annual mental health visits to NPs and PAs could not reliably be modeled. We estimated prediction equations for patient use of mental health services, regardless of who provided such services, as a proxy for use of psychiatric NPs and PAs. While total visits will overstate the actual number of visits where NPs and PAs provide services, this workload driver provides a scalar of how demand for services likely will grow over time and a scalar for level of demand across geographic areas. The decision to use total visits irrespective of provider type (e.g., primary care provider, psychiatrist office, psychologist office, other health provider) reflects two considerations. (1) NPs and PAs often provide mental health-related services to patients irrespective of the provider's area of specialization

(e.g., treating patients for depression during a primary care visit). (2) Certain patient characteristics might be correlated with visits to non-physicians instead of physicians (e.g., whether residing in a metropolitan area, insurance type including insured by Medicaid, and family income level).

The above prediction equations apply only to modeling services in provider office and outpatient settings. Different assumptions and prediction equations are used for modeling demand for these occupations in other care delivery or employment settings as summarized in Exhibit 14.

Model validation activities, discussed below, suggest that the prediction equations and resulting workforce demand projections capture much of the variation across states in demand for behavioral health services. The exception is that the prediction equations do not adequately capture variation across states in demand for addiction counselors. Specifically, when comparing (a) state-level estimates of 2016 demand for addiction counselors per 100,000 adults and per 100,000 youth and adolescents, to (b) state-level estimates of prevalence of substance use disorder (SUD) among the populations age 18 and older and age 12-17, there appears to be low correlation (i.e., correlation coefficient <0.2).[a] This low correlation suggests that patient characteristics not included in HWSM (e.g., illicit drug use and alcohol abuse) vary systematically by state and that the patient characteristics in the model (i.e., demographics, lifestyle variables, disease prevalence, family income, and insurance type) do not adequately explain need for addiction counselor services. An ongoing area of research for HWSM refinement is how predicted demand for substance abuse counselors differs by geographic area population density, as past research finds that prevalence and reasons for substance abuse treatment admissions differs by rural versus urban location.[65]

Therefore, state-level multiplicative scalars were used to adjust demand for addiction counselors to reflect state variation in SUD prevalence. To create the scalars, SUD prevalence for each state from SAMHSA's 2015 & 2016 National Survey on Drug Use and Health (NSDUH) was divided by the national average prevalence (Exhibit 12).[66]

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[a] Substance Use Disorder is defined as meeting criteria for illicit drug or alcohol dependence or abuse.

Exhibit 12: Substance Use Disorder in the Past Year, Age 12+ (2016-2017)

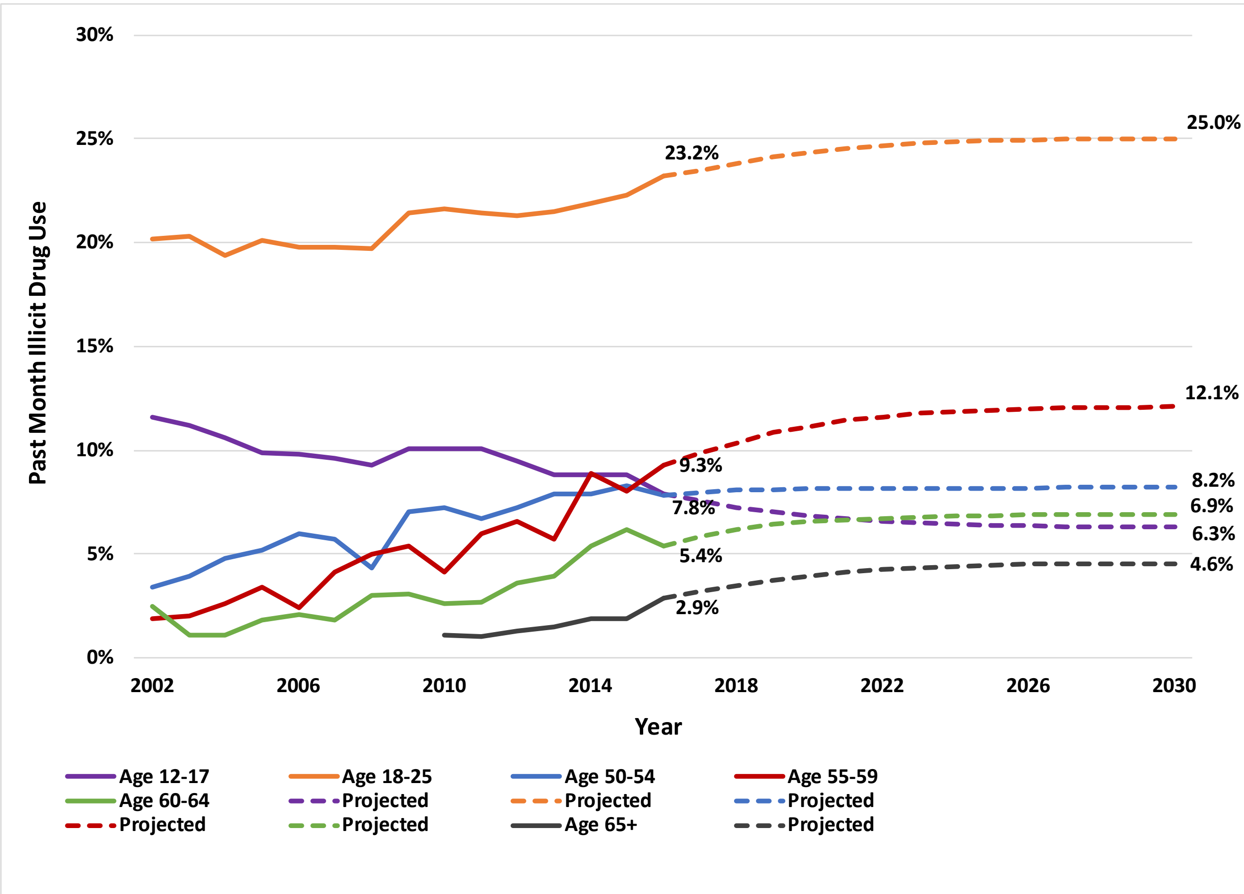
State	SUD Prevalence (%)	Scalar Adjustment for Addiction Counselors
Alabama	6.59	0.897
Alaska	8.98	1.222
Arizona	7.45	1.013
Arkansas	7.37	1.003
California	7.48	1.018
Colorado	8.76	1.191
Connecticut	8.40	1.143
Delaware	8.53	1.160
District of Columbia	11.21	1.524
Florida	6.95	0.945
Georgia	6.00	0.816
Hawaii	6.77	0.921
Idaho	7.79	1.060
Illinois	7.98	1.085
Indiana	7.14	0.972
Iowa	8.73	1.187
Kansas	6.92	0.941
Kentucky	7.12	0.968
Louisiana	8.02	1.091
Maine	8.08	1.099
Maryland	7.49	1.019
Massachusetts	9.64	1.312
Michigan	7.56	1.029
Minnesota	6.72	0.914
Mississippi	6.44	0.876
Missouri	7.29	0.992
Montana	8.98	1.221
Nebraska	7.69	1.045
Nevada	8.04	1.093
New Hampshire	8.32	1.132
New Jersey	6.23	0.847
New Mexico	8.01	1.089
New York	7.71	1.048
North Carolina	6.27	0.853
North Dakota	8.24	1.121
Ohio	7.67	1.043
Oklahoma	7.44	1.012
Oregon	9.39	1.277
Pennsylvania	6.88	0.935
Rhode Island	8.44	1.147
South Carolina	7.53	1.024
South Dakota	9.18	1.248
Tennessee	6.66	0.906
Texas	6.14	0.835
Utah	6.78	0.922
Vermont	9.64	1.311
Virginia	7.41	1.007
Washington	8.56	1.165
West Virginia	6.30	0.857
Wisconsin	8.13	1.106
Wyoming	7.80	1.061
US Average	7.35	1.000

Source: Center for Behavioral Health Statistics and Quality. Table 23. Substance Use Disorder in the Past Year, by Age Group and State: Percentages, Annual Averages Based on 2016 and 2017 NSDUHs. 2019.

If a state had 10% higher or 10% lower prevalence relative to the national average, the scalar would be 1.1 and 0.9, respectively. While these scalars changed the state-level projections, they had only a negligible effect on national projections when projected to 2030.

Historical data from NSDUH suggests that SUD prevalence among adults has been increasing steadily over the past 14 years, while prevalence has declined among the population age 12-17 (Exhibit 13). This trend continues in the projection model, but the modeled trend is non-linear and slows to a steady state over the next five years.

Exhibit 13: Substance Use Disorder in the Past Year, by Age Group



Source: National Survey on Drug Use and Health, 2002-2016 data.

Converting Demand for Visits to Demand for Providers

The approach to modeling demand for behavioral health workers is similar to the general approach described in Chapter III for other health workers. First, national estimates of total FTE providers in each care delivery setting were estimated. The primary source was the 2018 OES, with occupation-specific data sources used for psychiatrists, nurse practitioners, physician assistants and psychologists (Exhibit 14). Total workload measures were divided by FTE supply in 2017 to calculate staffing ratios by occupation and care delivery setting (Exhibit 15). The Baseline demand scenarios assumed that provider-to-visits ratio will remain unchanged during the projection period and behavioral health service delivery in each state followed the national patterns.

Exhibit 14: Distribution of Behavioral Health Workers across Employment Settings, 2017

Setting:	Hospitals	Emergency Department	Outpatient	Offices	Residential Care/Nursing Home	Schools	Academia	Other	Total *
Distribution									
Psychiatrists [a]	21%	3%	4%	73%	0%	0%	0%	0%	100%
Psychiatric technicians [b]	62%	0%	6%	3%	13%	2%	0%	15%	100%
Psychiatric aides [b]	46%	0%	0%	3%	18%	0%	0%	33%	100%
Psychologists [c]	13%	0%	10%	44%	1%	16%	4%	12%	100%
Nurse practitioners [d]	17%	2%	16%	30%	20%	1%	4%	10%	100%
Physician assistants [e]	33%	2%	33%	27%	0%	0%	0%	5%	100%
Addiction counselors [b]	11%	0%	24%	5%	23%	5%	0%	31%	100%
Social workers [f]	17%	0%	11%	3%	7%	9%	0%	54%	100%
Mental health counselors [g]	11%	0%	21%	13%	15%	3%	0%	37%	100%
School counselors [h]	0%	0%	0%	0%	0%	88%	0%	12%	100%
Marriage & family therapists [i]	0%	0%	19%	17%	8%	0%	0%	56%	100%
Numbers of Providers									
Psychiatrists [j]	9,860	1,210	1,910	34,670					47,650
Psychiatric technicians	43,990		4,050	2,260	9,080	1,250		10,740	71,360
Psychiatric aides	25,910			1,870	10,320			18,820	56,910
Psychologists	11,430		9,550	39,880	630	14,710	3,820	11,420	91,440
Nurse practitioners	1,730	210	1,720	3,160	2,120	80	450	990	10,460
Physician assistants	510	30	510	420				80	1,550
Addiction counselors	10,220		22,320	4,550	21,030	4,790		28,430	91,340
Social workers	40,550		26,130	6,240	15,740	22,180		128,580	239,410
Mental health counselors	15,620		30,090	17,970	21,680	3,670		51,750	140,760
School counselors						102,210		13,870	116,080
Marriage & family therapists			10,080	8,930	4,440			29,630	53,080

Notes: Standardized FTE definition, 1 FTE= 40 hours/week. * Numbers might not sum to totals due to rounding. [j] Incorporates 2017 national shortfall assumption of 5,906 additional psychiatrists needed to de-designate Mental Health Professional Shortage Areas.

Sources: [a] American Medical Association Master File, 2017. [b] Bureau of Labor Statistics Occupational Employment Statistics, 2018. [c] American Psychological Association licensing data,2015. [d] HRSA/NCHWA National Sample Survey of Nurse Practitioners, 2019. [e] Totals from BLS Occupational Employment Statistics, 2018 & estimate of percent in psychiatry from National Commission on Certification of Physician Assistants, 2018. [f] Totals from BLS Occupational Employment Statistics, 2018 & percentage with master's degree from American Community Survey, 2017. [g] NBCC licensing data, 2018. [h] State Non-Fiscal Public Elementary/Secondary Education Survey, 2017. [i] SAMHSA Behavioral Health,2012.

Exhibit 15: Summary of Behavioral Health Profession Workload Drivers: US Total 2017

<table>
<tr><th>Setting:</th><th>Hospitals</th><th>Emergency Department</th><th>Outpatient</th><th>Offices</th><th>Residential Care/Nursing Home</th><th>Schools</th><th>Academia</th><th>Other</th></tr>
<tr><td>Workload Metric</td><td>Days</td><td>Visits</td><td>Visits</td><td>Visits</td><td>Residents</td><td>Student</td><td>Graduates</td><td>Population</td></tr>
<tr><td>Psychiatrists</td><td rowspan="3">13,710,924</td><td>5,619,063</td><td rowspan="3">2,195,168</td><td rowspan="3">30,110,081</td><td rowspan="11">2,161,831</td><td rowspan="11">53,726,751</td><td rowspan="11">35,190,371</td><td rowspan="11">325,721,834</td></tr>
<tr><td>Psychiatric technicians</td><td>-</td></tr>
<tr><td>Psychiatric aides</td><td>-</td></tr>
<tr><td>Psychologists</td><td>152,265,510</td><td>-</td><td>728,737</td><td>52,989,763</td></tr>
<tr><td>Nurse practitioners</td><td rowspan="2">13,710,924</td><td rowspan="2">5,619,063</td><td>10,752,065</td><td>140,484,155</td></tr>
<tr><td>Physician assistants</td><td>1,949,238</td><td>32,646,843</td></tr>
<tr><td>Addiction counselors</td><td rowspan="3">152,265,510</td><td rowspan="5">-</td><td>7,969,331</td><td>154,414,064</td></tr>
<tr><td>Social workers</td><td>1,411,948</td><td>33,462,135</td></tr>
<tr><td>Mental health counselors</td><td>7,969,331</td><td>154,414,064</td></tr>
<tr><td>School counselors</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>Marriage & family therapists</td><td>-</td><td>7,969,331</td><td>154,414,064</td></tr>
<tr><td colspan="9">Staffing Ratios (national workload ÷ FTE providers)</td></tr>
<tr><td>Psychiatrists</td><td>1,391</td><td>4,652</td><td>1,149</td><td>868</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>Psychiatric technicians</td><td>312</td><td>-</td><td>542</td><td>13,353</td><td>238</td><td>43,016</td><td>-</td><td>30,325</td></tr>
<tr><td>Psychiatric aides</td><td>529</td><td>-</td><td>-</td><td>16,136</td><td>210</td><td>-</td><td>-</td><td>17,309</td></tr>
<tr><td>Psychologists</td><td>13,320</td><td>-</td><td>76</td><td>1,329</td><td>3,431</td><td>3,653</td><td>9,207</td><td>28,520</td></tr>
<tr><td>Nurse practitioners</td><td>7,925</td><td>26,631</td><td>6,266</td><td>44,513</td><td>1020</td><td>716,357</td><td>78,550</td><td>328,018</td></tr>
<tr><td>Physician assistants</td><td>26,779</td><td>175,596</td><td>3,807</td><td>77,731</td><td>-</td><td>-</td><td>-</td><td>4,175,921</td></tr>
<tr><td>Addiction counselors</td><td>14,893</td><td>-</td><td>357</td><td>33,974</td><td>103</td><td>11,226</td><td>-</td><td>11,455</td></tr>
<tr><td>Social workers</td><td>3,755</td><td>-</td><td>54</td><td>5,362</td><td>137</td><td>2,423</td><td>-</td><td>2,533</td></tr>
<tr><td>Mental health counselors</td><td>9,751</td><td>-</td><td>265</td><td>8,592</td><td>100</td><td>14,659</td><td>-</td><td>6,295</td></tr>
<tr><td>School counselors</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>526</td><td>-</td><td>23,481</td></tr>
<tr><td>Marriage & family therapists</td><td>-</td><td>-</td><td>790</td><td>17,286</td><td>487</td><td>-</td><td>-</td><td>10,994</td></tr>
</table>

Source: Projections for 2017 from HWSM

C. Primary Care Providers as a Source of Behavioral Health Services

This study looked at the current role of primary care providers (PCPs) in the delivery of behavioral health services, with PCPs playing several important roles:

1. **Screening**: Primary care is often the entry point to the health care system, so PCPs help screen patients and identify need for behavioral health treatment. The US Preventive Services Task Force (USPSTF) recommends that PCPs screen children, adolescents and young adults for behavioral health outcomes.[67,68] USPSTF also recommends screening and counseling in primary care settings for adults regarding excessive alcohol use and depression.[69,70]
2. **Treatment**: PCPs sometimes are involved in the direct treatment of patients—especially in areas without adequate behavioral health infrastructure to refer patients to other providers. Treatment includes counseling, prescribing medications for depression and anxiety, and even prescribing methadone to treat opioid use disorder.[71]
3. **Collaboration within multidisciplinary teams**: The growth in integration of behavioral health into primary care practices is increasing the number of PCPs who are part of multidisciplinary teams that include professional behavioral health providers.[72]

The research questions to address for this study were (a) What proportion of PCP time is spent providing behavioral health services? (b) What practice characteristics (e.g., rural location) are correlated with the proportion of time PCPs spend providing behavioral health services? (c) Is the proportion of time PCPs spent providing behavioral health services projected to change over time?

To address research questions (a) and (b), two analyses were conducted. Visits to primary care offices in 2016 NAMCS data were analyzed with respect to behavioral health diagnoses and physicians' patient care time. Additionally, the proportion of behavioral health services provided by PCPs and the proportion of PCP time that is categorized as a behavioral health visit were analyzed in the 2017 Medicare data.

NAMCS is based on a representative sample of physician office visits, and for each participating physician practice information was collected for a random sample of patient visits obtained through record extraction. Among the information collected for each visit are the type of physician seen, the length of time (in minutes) the physician spent with the patient, and up to five diagnosis codes. The NAMCS sampling frame includes three specialties categorized as primary care: family medicine, general internal medicine, and general pediatrics. Analysis of primary care physician time indicates that 15.5% of their direct patient care time was spent with patients who had at least one visit diagnosis code for a behavioral health condition (Exhibit 16).[a] This percentage ranged from a high of 19.6% for internal medicine to a low of 10.4% for pediatrics.

The percentage of primary care physician direct patient care time spent with patients where the primary diagnosis associated with the visit was for behavioral health were also calculated by specialty. The percentage for primary care physicians overall was 7.4%, ranging from a high of 8.5% for pediatrics to a low of 5.9% for internal medicine. These findings suggest that for most visits to a pediatrician where there is a behavioral health diagnosis, it is usually the primary diagnosis. On the other hand, for most visits to a general internist where there is a behavioral health diagnosis, it usually is not the primary diagnosis.

For patients with multiple diagnoses for the visit there is insufficient information to know what proportion of physician time was spent addressing behavioral health diagnoses. Consequently, the visit time was pro-rated by dividing total behavioral health diagnoses by total diagnoses. Hence, if a 15-minute visit had three diagnoses and one was behavioral health, then one third (5 minutes) of the visit was counted as time spent providing behavioral health services. Note that for care where a physician provides screening or counseling for behavioral health services there is not necessarily a behavioral health diagnosis. Using this approach, overall, 5.8% of primary care physician time in direct patient care was spent providing behavioral health services. If we use this 5.8% as an estimate of total physician time (direct and indirect patient care) associated with providing behavioral health services, then when multiplied by the estimated 226,000 primary care physicians in 2017[15] this equates to approximately 13,100 FTE primary care physicians providing behavioral health services—27.5% of the size of the entire psychiatrist workforce in 2017. The NAMCS data is insufficient to calculate the proportion of primary care NP and primary care PA time spent providing behavioral health services.

Exhibit 16: Percentage of Primary Care Physician Direct Patient Care Time in Visits Providing Behavioral Health Services

	Visits with Any Behavioral Health Diagnosis	Visits Where Primary Diagnosis is Behavioral Health Diagnosis	Pro-rated Visit Time Providing Behavioral Health Services
Family Medicine	16.4%	7.4%	5.3%

[a] ICD-10 diagnosis codes that begin with "H" identify behavioral health diagnoses.

Internal Medicine	19.6%	5.9%	8.0%
Pediatrics	10.4%	8.5%	5.5%
Total	**15.5%**	**7.4%**	**5.8%**

Among visits where the primary diagnosis was for behavioral health services:

- 33% of the visits were for attention deficit disorders
- 18% of the visits were for major depressive disorder—most for single episode (14%) versus recurrent condition (4%)
- 17% of the visits were for other anxiety disorders
- 17% of visits were for opioid related disorders—however, 25% of visits in non-metropolitan areas were for opioid related disorders versus 14% of visits in metropolitan areas.

When behavioral health was listed as the second diagnosis code, 39% were for “other anxiety disorders,” 16% for “major depressive disorder” (15.5% for single episode and 2.5% for recurring), with smaller percentages for other conditions including 3.3% of visits for opioid related disorders. Across all diagnosis codes for a visit, primary care physician time spent addressing substance abuse disorders is estimated at 1.1% in metropolitan areas and 1.9% in non-metropolitan areas.

The second analysis looked at 2017 Medicare data, which contains data on diagnosis categories and type of physician providing care. Because different types of care require differing levels of physician time and expertise, work relative value units (WRVUs) were used as a proxy for physician time.[a] The analysis focused on the care categorized as “specialty-psychiatry” visits, finding that 18.8% of physician-generated specialist psychiatry WRVUs was billed by primary care physicians—versus 78.2% by psychiatrists and 3.0% by other physicians (e.g., emergency medicine, addiction medicine). Analysis of this data did not provide insights into the proportion of primary care physician time spent providing behavioral health services, and much of the care in this database was categorized with generic terms such as “office visits-established.” For example, when looking at the services provided by psychiatrists only 30% of their WRVUs was

[a] An area for ongoing research is whether WRVU or another measure of provider resource use per visit, such as number of minutes per physician-patient encounter as measured in the National Ambulatory Medical Care Survey, can improve the prediction equations from MEPS which currently count all visits to a provider specialty/occupation equally. To the extent that older adults have more health conditions than younger adults, the length of an ambulatory visit could differ systematically by demographic.

categorized as specialty-psychiatry, with much of their WRVUs listed under categories such as “office visits” and “hospital visits.”

In summary, approximately 5.8% of primary care physician time is spent providing behavioral health services, equivalent to approximately 13,100 FTE primary care physicians. Approximately 2,600 FTEs are specifically to address substance abuse disorders, and the remaining 10,500 FTEs for mental health—primarily to address anxiety disorders, major depressive disorders, and attention-deficit hyperactivity disorders.

D. Validation Activities

International Society for Pharmacoeconomics and Outcomes Research (ISPOR) guidelines on best practices for model validation activities[73] were followed. Validation of HWSM in general is discussed in Chapter XI. For the behavioral health component of HWSM, validation activities include the following:

- Subject matter experts— including health workforce researchers from two HRSA-funded health workforce centers and representatives from nine associations that represent the behavioral health occupations modeled—were engaged to review data inputs and preliminary findings.
- The workforce demand projections were compared to external data sources not used by HWSM to develop the projections to evaluate the state-level projection. Specifically, for the behavioral health workforce projections, the state-level demand projections were compared to various state-level measures for mental health and substance use disorder using correlation coefficients between estimates at the state level. To make the comparisons across metrics, the demand projections were divided by size of the state’s population to calculate demand per 100,000 population. Number of days with depression/anxiety in the past 30 days data from Behavioral Risk Factor Surveillance System (BRFSS) is one metric for comparison. Other metrics come from SAMHSA’s NSDUH—including adult prevalence of any mental illness (AMI), adult prevalence of serious mental illness (SMI), youth & adolescent prevalence of major depressive episode (MDE), and adult and youth & adolescent SUD prevalence. Variation across states in the severity of AMI was estimated from online depression screening data (n=27,511, data collected May 2014-Dec 2016) that reports the proportion of depression cases that are minimal, mild, moderate, moderately severe, and severe by state.[74]

Correlation coefficients were used to estimate the linear correlation between HWSM demand estimates and the comparison metrics for each state. Most of the estimated correlation coefficients (Rs) suggest moderate (R>0.5) to strong (R>0.7) relationships—where R=1.0 represents perfect correlation between the demand projections and the comparison metrics, and R=0 represents no correlation. Examples of these correlations include the following:

- Psychologist demand is highly correlated with AMI prevalence adjusted for depression severity (R=0.76). The correlation is moderate with SMI prevalence (R=0.63) and BRFSS prevalence data on self-reported days with depression/anxiety (R=0.54)
- Psychiatrist demand is moderately correlated with AMI prevalence adjusted for depression severity (R=0.60), with SME prevalence (R=0.51) and with correlated with BRFFS self-reported days with depression/anxiety (R=0.64)
- External metrics of need for behavioral health services are not perfectly correlated with each other. NSDUH-derived prevalence for AMI, MDE, and SMI are highly correlated across states with R=0.85 for these comparisons (perhaps reflecting in part the methods used to construct these prevalence estimates). AMI prevalence from NSDUD has a weak correlation with the BRFSS-derived metric on prevalence of self-reported days with depression/anxiety (R=0.32).

As discussed previously, demand estimates for addiction counselors had little correlation with SUD prevalence for both adults and for youth and adolescents. Hence, the state-level multiplicative scalars were used to better capture state-level variation in factors contributing to demand for addiction counselors.

VI. General Surgeon Model Components (updated 2019)

This chapter describes adaptation of HWSM to model supply and demand for general surgeons. This work is in response to Senate Report 115-289:[75]

> *Congress urges HRSA, to study access by underserved populations to general surgeons and provide a report to the Committee 18 months after enactment detailing potential surgical shortages, especially as it relates to geographic location (i.e., rural, urban, and suburban). For the report to the Committee, HHS should consult with relevant stakeholders, including medical societies, organizations representing surgical facilities, organizations with expertise in general surgery, and organizations representing patients.*

The research team reached out to key stakeholders with the goals to identify the best available data sources, discuss trends affecting general surgery workforce supply and demand, and provide the opportunity for feedback on preliminary findings. The research team met with the American College of Surgeons to share preliminary findings and solicit feedback. The information provided in this technical documentation and in HRSA reports does not necessarily reflect the views of the organizations that responded to our invitation to participate in the workforce study and there may not be clear consensus on all assumptions. Other organizations representing surgeons, surgical facilities, and patients were contacted, but these organizations did not express interest in participating.

A. Modeling Supply

Estimating the Base Year Workforce Supply

Estimates of the starting supply of general surgeons come from the 2017 American Medical Association Masterfile. Key variables include physician age, sex, activity status, and primary work location (which was mapped to state and county). The Masterfile contains information on physicians' first and second specialties. This analysis categorized physicians in the Masterfile as general surgeons if they self-identified "general surgery" as their first specialty and claimed no second specialty (20,120 FTE physicians).

This approach captures physicians who solely practice general surgery. This approach may not capture a small subset of surgical specialists and subspecialists who may serve in many clinical roles for their communities, and in particular who may provide some part-time level of general surgery services to communities facing physician shortages. However, neither the Masterfile nor other recognized workforce data sources provide FTE level of effort information to allow such a detailed level of analysis (e.g., 6 hours of weekly general surgery procedure time by a full-time vascular surgeon). Thus, in order to ensure accuracy and consistency, only data for self-reported general surgeons as the primary specialty provided the basis for the following health workforce projection findings. Although the Masterfile is a widely used source of physician workforce statistics, the self-reported nature of this data is another limitation of its use for workforce analyses. The HRSA HWSM technical report provides additional details on the physician supply modeling process and the data sources used in the HWSM.

Modeling New Entrants

To model additions to the workforce each projection year, a synthetic population was created from which new entrants are drawn for the simulation such that the number of newly created individuals reflects the annual number and demographics of recent new graduates. The AMA Masterfile contains the year each general surgeon completed his or her graduate medical education; the distribution of new graduates between 2010-2017 by state, age, and sex defines the demographic distribution of new surgeons for the projection simulation. New surgeons were also assigned a rurality level based on the rurality distribution of general surgeons who recently completed training.

Modeling Workforce Participation

For general surgeons age 50 and over the probability of retirement in any projection year was modeled based on analysis of Florida's 2012-2013 Physician Survey, wherein physicians were asked about their intention to retire over the upcoming three years.[a] The attrition probabilities are specific to general surgeons and increase with age, but sample size was insufficient to model attrition by physician sex. The projections assume no attrition from the national surgeon labor force for surgeons under age 50. While there is insufficient data to estimate attrition prior to age 50, attrition among surgeons under age 50 likely is very small.

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[a] Efforts continue to find improved data sources for modeling physician attrition patterns. One potential future source is a survey of physicians recently conducted by the Association of American Medical Colleges which collects information on physician retirement intentions. Past analyses have compared the age distribution of physicians across subsequent years of the AMA Masterfile, but there were concerns that due to the lag between physicians leaving the workforce and when that information becomes available in the Masterfile that attrition patterns were under-stated.

Modeling Hours Worked

Hours worked patterns were estimated from regression analysis of survey data for general surgeons across four states (FL, SC, NY, MD) covering the period 2012-2018.[a] The dependent variable was hours worked per week in patient care activities, with explanatory variables consisting of dichotomous variables[b] for 5-year age groups and sex, as well as interaction terms between age group and sex. Supply projections reflect the changing demographics of the workforce and differing average hours worked per week based on surgeons' age and sex. The expected number of hours worked weekly by each simulated surgeon was converted to FTE supply by dividing the person-hours worked by 40. This creates a uniform standard of 1 FTE as working 40 hours per week, but also means that the baseline FTE generated by HWSM can differ from the actual count of general surgeons employed.

B. Modeling Demand

This section discusses issues specific to projecting demand for general surgeons. See Chapter III for a discussion of the general approach to modeling demand for health care services and providers employed by the HWSM.

The demand analysis models current patterns of health care use, including office and outpatient visits to general surgeons as well as emergency visits and hospitalizations requiring surgery. Demand for surgery-related services is then used to model demand for general surgeons, and takes into consideration geographic variation in the availability of specialty surgeons, which may increase or decrease demand for general surgeons. The microsimulation approach models demand for health care services by using individual-level (micro) data on predictors of health care use for each person in a representative sample of a designated geographic region (national, state, or county-equivalent). The three-part modeling process (1) constructs a representative sample of the population in each county; (2) estimates the use of surgery-related services by this population, by applying factors from a set of regression models to estimate current, national-level average health care utilization patterns for a population having certain demographic, geographic, and health status characteristics; and (3) models general surgeon workforce for the delivery of services demanded. **d**

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[a] State survey data is used for modeling hours worked, rather than the ACS which is used for modeling hours worked for many occupations, because ACS does not identify physician specialty and hours worked patterns vary substantially by specialty.

[b] Dichotomous variables take on the value of 1 if the person is in that specified group, and 0 otherwise.

VII. Allied Health & Select Other Occupations Model Components (updated 2018)

This chapter summarizes efforts to adapt HWSM to model supply and demand for select allied health occupations and several other occupations (e.g., podiatrists, audiologists). Because of data limitations, discussed later, supply projections could only be made for 11 of the 26 occupations included in this component of the HRSA workforce modeling effort (Exhibit 17).

Exhibit 17: Allied Health and Select Other Occupations Modeled

Occupation Categories	Supply Modeled	Demand Modeled
Therapeutic Services		
Chiropractors	Yes	Yes
Podiatrists	Yes	Yes
Radiation therapists	No	Yes
Rehabilitation Services		
Occupational therapists	Yes	Yes
Occupational therapy assistants	No	Yes
Occupational therapy aides	No	Yes
Physical therapists	Yes	Yes
Physical therapist assistants	No	Yes
Physical therapist aides	No	Yes
Respiratory Care Services		
Respiratory therapists	Yes	Yes
Vision and Hearing Services		
Optometrists	Yes	Yes
Opticians	Yes	Yes
Audiologists	Yes	Yes
Pharmacy Services		
Pharmacists	Yes	Yes
Pharmacy technicians	No	Yes
Pharmacy aides	No	Yes
Dietary and Nutrition Services		
Dietitians	Yes	Yes
Nutritionists	No	Yes
Dietetic technicians	No	Yes
Emergency Medical Technician and Paramedic Services		
Emergency medical technicians and paramedics	No	Yes
Diagnostic Laboratory Services		
Medical and clinical laboratory technologists	Yes	Yes
Medical and clinical laboratory technicians	No	Yes
Diagnostic Imaging Services		
Diagnostic medical sonographers	No	Yes

Nuclear medicine technologists	No	Yes
Radiologic technologists	No	Yes
Community Health Worker Services	No	Yes

For this update, the research team reached out to professional associations representing behavioral health professions to identify the best available data sources, discuss trends affecting workforce supply and demand, and to provide the opportunity for feedback on preliminary findings. The information provided in this technical documentation and in HRSA reports does not necessarily reflect the views of the associations that responded to our invitation to participate in the workforce study and there may not be clear consensus on all assumptions. Individuals from the following associations participated:

- Academy of Doctors of Audiology (ADA)
- Academy of Nutrition and Dietetics (AND)
- American Association for Respiratory Care (AARC)
- American Chiropractic Association (ACA)
- American Occupational Therapy Association (AOTA)
- American Optometric Association (AOA)
- American Podiatric Medical Association (APMA)
- American Society of Radiologic Technologists (ASRT)
- National Registry of EMTs (NREMT)
- Society of Diagnostic Medical Sonography (SDMS)
- Society of Nuclear Medicine and Molecular Imaging (SNMMI)

A. Modeling Supply

For the eleven occupations where there is sufficient data to project future supply, we modeled multiple scenarios. A status quo scenario extrapolates current trends in supply determinants: number and characteristics of current and new providers, hours worked patterns, and attrition patterns Alternative scenarios modeled the sensitivity of future supply to changes in key trends and assumptions—including (a) ±10% change in annual numbers of new graduates entering the workforce, and (b) if attrition patterns were to change such that providers retired up to two years earlier or delayed retirement by up to two years, on average, relative to historical retirement patterns.

Estimating the Base Year Workforce Supply

The primary sources for data on current number and characteristics for the occupations modeled came from pooled 2012-2016 ACS data supplemented with OES data and licensure counts from specialty associations. We pooled multiple years of ACS data to create a larger sample for each state to produce estimates of the demographic distribution of current supply by age, sex, and race/ethnicity. The counts for number of dieticians came from the Academy of Nutrition and Dietetics, which allows for modeling a more precise category than the SOC category (dieticians and nutritionists) in ACS or OES. The state-level counts for the number of podiatrists came from the American Podiatric Medical Association (APMA), which are based on licensure files, while the counts for radiation therapists came from the American Registry of Radiologic Technologists' census from September 2016.

Modeling New Entrants

The primary source for estimating annual numbers of new entrants in each occupation was the 2016 Integrated Postsecondary Education Data System (IPEDS), supplemented with data provided by the specialty associations. As described in Section Modeling Supply of Health Professionals II.B, new entrants were added to the workforce via a "synthetic" cohort. The size of the cohort was based on the number and characteristics of recent graduates in each occupation. The number of new entrants for radiation therapists used the American Registry of Radiologic Technologists' data on radiation therapy exams taken in 2017.

Each new worker was assigned an age, race, and sex that reflected the distributions seen in recent years (Exhibit 18). To estimate the percent female, we used 2012-2016 ACS data on providers age 30-39 as an approximation of the newer cohort in that occupation. To calculate the age distribution of new entrants to the workforce, we compared consecutive years of ACS data to compare the number of providers of a particular age (e.g., age 29) to the number of providers in the subsequent ACS annual file who were one year older (e.g., age 30). The subsequent ACS file contains information on the workforce from the previous year plus any additions or subtractions to the workforce. In the above example, to the extent that the number of providers age 30 in 2016 exceeds the number of providers age 29 in 2015, this difference reflects the net number of new providers entering the workforce at age 29-30. With this information, we estimated the age distribution of new entrants to the workforce and used multiple years of data to increase sample size by individual age and occupation.

The number of new entrants and their age-sex distribution were assumed to remain constant during the projection period. For opticians, an additional 1,698 new graduates were added to the number of IPEDS graduates to estimate the number of additional new opticians that need to join the workforce annually for the optician workforce to grow at rates consistent with OES historical trends. This reflects multiple training paths to become an optician—including on the job training or an apprenticeship as an alternative to pursuing an educational certificate or degree.

Some occupations such as aides, assistants or technicians have data limitations that preclude making projections of future supply. For occupations that do not require licensure or that have few educational or training requirements there is insufficient data on the number of people newly entering these occupations. Likewise, occupations with easy entry often have high turnover rates creating challenges to obtain reliable supply forecasts.

Exhibit 18: Number and Demographics of New Entrants to Select Health Care Occupations

Occupation	Annual Graduates [a]	Female (%) [b]	Race/Ethnicity (%) [b]				Age Distribution (%) [b]			
			White	Black	Other	Hispanic	≤25	26-30	31-40	≥41
Dietary and Nutrition Services										
Dietitians	4,157	89	81	9	10	<1	6	42	15	37
Pharmacy Occupations										
Pharmacists	14,665	65	69	5	25	1	8	55	20	17
Rehabilitation Services										
Occupational therapists	6,191	89	84	4	11	1	7	48	24	21
Physical therapists	9,710	71	77	3	19	1	9	53	31	6
Respiratory Care Services										
Respiratory therapists	7,059	70	74	11	13	2	2	50	39	9
Therapeutic Services										
Chiropractors	2,418	37	86	89	10	1	1	35	42	11
Podiatrists	544	48	84	9	7	<1	<1	<1	81	19
Radiation Therapists	904	69	86	5	9	<1	2	65	24	10
Vision and Hearing Services										
Opticians	2,306	76	77	7	15	1	1	44	25	30
Optometrists	1,652	62	74	1	25	<1	7	37	25	32
Audiologists	502	89	97	<1	3	<1	3	42	46	9

Source: [a] 2016 IPEDS for annual new graduates, except radiation therapists which uses figures from ARRT and opticians which uses incorporates estimates of additional new entrants to the workforce to reflect on-the-job/apprenticeship as an alternative entry path to certification or education. [b] 2012-2016 ACS analysis of workers.

Modeling Workforce Participation

Labor force participation rates for health professionals were calculated directly for individuals under age 50 using ACS data. The analysis used information on whether the person was active in the workforce—defined as working at least 1 hour per week in their profession. Each simulation year, the model selects some health professionals in the under 50 age group to become inactive and thus count for 0 supply. However, these individuals remain part of the supply model and are eligible to become active again in the following simulation year. For health professionals age 50 and over we modeled the probability of retiring, with the probability increasing with age. Attrition patterns for each profession were based on ACS data and were constructed based on a question asking whether the person is currently employed, and whether they were employed last year. Health professionals flagged for attrition drop out of the supply entirely and do not return in later years.

Modeling Hours Worked

We used Ordinary Least Squares regression to model hours worked patterns for each health occupation. The dependent variable was total hours worked in the previous week. Explanatory variables consisted of age group, sex, race, and a year indicator (as the ACS pooled data from 2012-2016).

Estimates and projections take into consideration the changing demographics of the workforce and that average hours worked per week differ by age, sex, race, and occupation. Then, the expected number of hours worked by each professional was converted to FTE supply by dividing the total person- hours worked by 40. This creates a uniform standard of 1 FTE as working 40 hours per week regardless of the occupation, but does mean that the initial FTE of an occupation can differ from the actual count of persons employed in the occupation.

Modeling State-Level Supply and Migration

Health occupations often have different levels of surplus and shortage in different parts of the United States. To better estimate this, HWSM includes state-level supply estimates where sufficient data is available. In the ACS and OES, some occupations do not have totals reported in every U.S. state, so state-level supply estimates are unavailable for these occupations. Occupations affected include chiropractors, podiatrists, radiation therapists, and audiologists.

For occupations with sufficient state-level data, HWSM models for future movement of health professionals across states. This is accomplished in two steps. First, a logistic regression on ACS data estimates the probability of migrating to any other state for the under 50 population as a function of age group, sex, race, the current state's population, and a year indicator. Then, the simulation randomly assigns each professional a probability of moving based on their demographic characteristics, and assigns those who move a new state based on the destination state distribution observed in ACS data for professionals who changed residence states.

B. Modeling Demand

Chapter III provides an overview of the data sources and approach to model demand for health care services and providers. In this chapter, we provide additional detail of analyses specific to modeling demand for the health occupations covered in this analysis.

We modeled demand for providers in allied health and selected other occupations under two scenarios:

1. The **status quo scenario** models what future demand would be if current care use and delivery patterns remained unchanged but accounts for changing demographics and variation across individuals in patterns of seeking health care services.
2. The **evolving care delivery system scenario** models trends in the health care system that have the potential to change how care is used and delivered over time.

Status Quo Demand Scenario

The status quo scenario starts with the assumption that national supply and demand currently are roughly in equilibrium and extrapolates current patterns of care into the future. Predicted probabilities of health care use were applied on the simulated micro-data set for future years to obtain projected health care service use specific to the settings where these professionals are employed.

Demand for workers in many occupation categories (e.g., therapeutic services, rehabilitation services, respiratory care services, and vision and hearing services) are based on rates of patient-clinician encounters across care delivery settings. Primary data sources analyzed include MEPS, NIS, NAMCS, and NHAMCS. Demand for pharmacists and pharmacy technicians and aides was tied to number of prescriptions written during patient visits to provider offices, out-patient clinics, according to ACS industry distribution mapped to employment settings (see appendix, Exhibit A-1). Data on the number of medications prescribed from the 2013-2015 NAMCS, and 2007-2011 NHAMCS were used to model the number of prescriptions that an individual would receive. These were aggregated for the entire population. Demand for diagnostic services was based on the overall growth in health care use (e.g., ambulatory visits, inpatient days).

The number of health workers employed in a setting in the base year was assumed to reflect demand for services in that setting. Therefore, projections of future demand for providers were based on the 2016 ratio of providers to services. The information on the distribution of employment across care settings came from the 2012-2016 5-year American Community Survey database. Exhibit A-1 in the Appendix provides detailed data on employment setting, workload and staffing-ratios by provider type.

Evolving Care Delivery Scenario

The evolving care delivery scenario builds on the status quo scenario that models changes in demand due to changing demographics. This scenario is described in Section III.D, but in this Section we provide additional detail on trends and factors that could affect demand for the allied health occupations modeled.

Achieving the modeled population health outcomes on a national basis would require increased levels of counseling by dietitians and nutritionists, and increased access to and adherence to medications that could increase demand or pharmacy services (though weight loss and other improvements in patient health would reduce demand for some types of pharmaceuticals by preventing or delaying on set of chronic disease and other adverse health outcomes).

A second component of this scenario is around providing a continuum of care across care delivery settings and coordinating multidisciplinary care. The goals of this principle are to efficiently and effectively shift care from higher cost to lower cost settings, to shift care from higher cost to lower cost providers, and to avoid unnecessary care. While there is a growing body of literature on this topic, a limitation of this literature is whether findings from specific interventions or populations can be generalized to a broader population and how to translate published findings into a scenario that can be modeled.[93]While there is a growing body of literature on this topic, a limitation of this literature is whether findings from specific interventions or populations can be generalized to a broader population and how to translate published findings into a scenario that can be modeled.[93] Likewise, different types of interventions can have overlapping outcomes, and it is unclear whether the impacts from multiple interventions are additive or complementary. For this scenario, we modeled a 5% reduction in hospital inpatient and ED utilization gradually through 2025, with a corresponding 5% reduction in the health workforce that supports patient care in these settings. We think the 5% decline assumption is conservative, and the potential impact is larger. Over the past decade there have been substantial declines in per capita use of hospital-based services as national attention has focused on efforts to preventive care to reduce avoidable hospital care and to shift care from hospitals to appropriate ambulatory settings. The magnitude of this 5% reduction assumption is supported by a growing body of literature exploring how different types of interventions and care delivery models can change patient health care needs and care utilization patterns. Examples include the following:

- **Reduced risk of hospitalization and rehospitalization**: Participation in a PCMH team-based intervention reduced rehospitalization rates from 18.8% to 7.7%.[94] Another study reports that PCMH reduced hospitalizations for PCMH-targeted conditions by 13.9% versus a 3.8% reduction in hospitalizations for other conditions.[91] Project RED (Re-Engineered Discharge), BOOST (Better Outcomes for Older adults through Safe Transitions), and other interventions have used team-based care to patients discharged from hospitals with the goal of reducing rehospitalization. Many of these interventions used nurse practitioners, nurses, social workers, physician assistants, and other health workers to ensure patients and their families receive appropriate counseling and follow-up care to reduce rehospitalization risk. AHRQ reports that RED reduced 30-day all cause rehospitalization by 2 percentage points (or about 11%, dropping from 18.6% to 16.6% readmission rate).[95] Similarly, BOOST appears to reduce hospital readmission rates by about 2 percentage points (or about 13.6% among implementation hospitals).[a] Much of the literature on reducing avoidable hospitalization is disease-specific (e.g., cardiology, pulmonology, diabetes, asthma, cancer, and behavioral health).[96–99] **Reduced risk of hospitalization and rehospitalization**: Participation in a PCMH team-based intervention reduced rehospitalization rates from 18.8% to 7.7%.[94] Another study reports that PCMH reduced hospitalizations for PCMH-targeted conditions by 13.9% versus a 3.8% reduction in hospitalizations for other conditions.[91] Project RED (Re-Engineered Discharge), BOOST (Better Outcomes for Older adults through Safe Transitions), and other interventions have used team-based care to patients discharged from hospitals with the goal of reducing rehospitalization. Many of these interventions used nurse practitioners, nurses, social workers, physician assistants, and other health workers to ensure patients and their families receive appropriate counseling and follow-up care

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[a] The authors report: *The average rate of 30-day rehospitalization in BOOST units was 14.7% prior to implementation and 12.7% 12 months later (P = 0.010), reflecting an absolute reduction of 2% and a relative reduction of 13.6%. Rehospitalization rates for matched control units were 14.0% in the preintervention period and 14.1% in the postintervention period (P = 0.831). The mean absolute reduction in readmission rates in BOOST units compared to control units was 2.0% (P = 0.054 for signed rank test comparing differences in readmission rate reduction in BOOST units compared to site-matched control units).*

to reduce rehospitalization risk. AHRQ reports that RED reduced 30-day all cause rehospitalization by 2 percentage points (or about 11%, dropping from 18.6% to 16.6% readmission rate).[95] Similarly, BOOST appears to reduce hospital readmission rates by about 2 percentage points (or about 13.6% among implementation hospitals).[a] Much of the literature on reducing avoidable hospitalization is disease-specific (e.g., cardiology, pulmonology, diabetes, asthma, cancer, and behavioral health).[96–99]

- **Reduced emergency department use by redirecting avoidable ED visits to appropriate primary care and community-based settings**: Estimates of avoidable ED visits vary by definition of "avoidable" and by patient population. One study estimated that between 13.7% and 27.1% of non-emergent ED patients could have been managed at an urgent care center or retail clinic.[100100] Other studies consider some emergent visits avoidable (e.g., stroke, myocardial infarction) if appropriate preventive care could have prevented the incident. A study by Truven analytics suggest that 71% of ED use is potentially avoidable in the sense that the care could be appropriately treated elsewhere, the medical condition necessitating the visit could have been treated to prevent the event from occurring, or the care was unnecessary.[101] A study by Kaiser Permanente Northern California found that for low-risk patients, ED physician brief phone follow-up or mailed information about alternative service options reduced patients' subsequent (6-month) ED utilization by 22% for patients age 65 years or older, and by 27% for patients under age 65.[102101] A study by Kaiser Permanente Northern California found that for low-risk patients, ED physician brief phone follow-up or mailed information about alternative service options reduced patients' subsequent (6-month) ED utilization by 22% for patients age 65 years or older, and by 27% for patients under age 65.[102] One study reports that transition to PCMH status was associated with 5–8% reductions in ED utilization among chronically ill patients, with the largest reductions in ED visits among patients with diabetes and hypertension, but no change in ED utilization among patients without chronic disease.[103103] Another study reports that PCMH reduced ED visits for PCMH-targeted conditions by 17.2% versus a 3.1% reduction in ED visits for other conditions.[9191]

A challenge with using the literature to model a scenario around avoidable ED and hospital use is that activities to divert care from costly hospital settings might simply change where the care is provided but not necessarily reduce overall demand for health workers.

- **Shift care from higher-cost to lower-cost providers**: There are multiple challenges facing health care systems today, including the rising cost of health care services and health workforce shortages. A strategy that has been pursued to address both the issue of rising costs and workforce shortages is task performance substitution. This is widely documented in the literature for physician assistants (PAs) and advanced practice nurses (APNs) performing tasks that historically were carried out by physicians.[104] Among the occupations covered in this report, shifting care among occupations pertains to occupational therapists (OT), OT assistants, and OT aides; physical therapists (PT), PT assistants, and PT aides; pharmacists, pharmacy technicians, and pharmacy aides; and dietitians, nutritionists, and dietetic technicians. Some studies have been carried out to determine the impacts that substitutions have had on costs and outcomes in allied health occupations, although the evidence base in the US is not particularly robust, with the majority of studies being carried out in Australia.

Providing pharmacy services in a community setting has been noted to improve patient outcomes and decrease health care costs, but expansion of these service offerings is often challenged by time constraints for dedicated patient care, or workload burdens.[105–109] The SafeMed program seeks to overcome this challenge and improve transitions of care by using lower-cost health workers, particularly certified pharmacy technicians as community health workers (CPhT-CHWS).[110] These workers provide medication management services to high-utilizer patients with multiple chronic conditions by serving as pharmacist extenders. This program achieved positive trends in outcomes such as increasing home visit completion rates within three days of discharge from 46.9% to 68.5%, and coordinated with pharmacists to increase outpatient comprehensive medication review, rising from a monthly average of 1.9 in 2013 to 7.9 in 2014. The study suggests that using these lower-cost workers in these roles can prove beneficial, although further exploration of the impact on clinical outcomes and health care use is still required and there is insufficient information for modeling demand scenarios around substitutability.Providing pharmacy services in a community setting has been noted to improve patient outcomes and decrease health care costs, but expansion of these service offerings is often challenged by time constraints for dedicated patient care, or workload burdens.[105–109] The SafeMed program seeks to overcome this challenge and improve transitions of care by using lower-cost health workers, particularly certified

pharmacy technicians as community health workers (CPhT-CHWS).[110] These workers provide medication management services to high-utilizer patients with multiple chronic conditions by serving as pharmacist extenders. This program achieved positive trends in outcomes such as increasing home visit completion rates within three days of discharge from 46.9% to 68.5%, and coordinated with pharmacists to increase outpatient comprehensive medication review, rising from a monthly average of 1.9 in 2013 to 7.9 in 2014. The study suggests that using these lower-cost workers in these roles can prove beneficial, although further exploration of the impact on clinical outcomes and health care use is still required and there is insufficient information for modeling demand scenarios around substitutability.

A third component of this scenario is increased use of **value-based insurance design** to increase use of high-value, under-utilized services by removing access barriers (usually by lowering the cost of such care) and decrease use of low-value, over-utilized services by raising access barriers (usually by raising the cost of such care). A 2014 Aon Hewitt survey found that only about 25% of U.S. employers are currently using or adding VBID for medical and pharmacy plans, but that within 3-5 years 59% of employers plan to add VBID for medical plans and 57% plan to add VBID for pharmacy plans.[111] For scenario modeling, we assume that VBID coverage will gradually increase to 100% coverage by 2025.[111] For scenario modeling, we assume that VBID coverage will gradually increase to 100% coverage by 2025.

VBID could potentially affect demand for a wide range of health workers—though based on the published literature the impact of VBID on health workforce demand is likely to be small. VBID simultaneously increases demand for some services and pharmaceuticals while decreasing demand for other services and pharmaceuticals which mitigates the workforce demand impact. The following highlights allied health and select other occupations where VBID could affect demand for services.

1. **Pharmacy occupations**: Numerous studies suggest that VBID increases overall medication adherence—which in turn could increase demand for pharmacists, pharmacy technicians and pharmacy aides. Improved adherence is associated with greater use of medications as proscribed by a health provider, though a variety of metrics have been used to measure adherence. A review of 20 studies on VBID for pharmaceuticals suggested average increased medication adherence of 3.4% after one year.[112] Few studies explore the impact beyond one year. A study of medication refill records for 74,748 individuals covering 8 drug classes over 2 years found that medication adherence increased by 1.4% to 3.2% (midpoint 2.3%) at one year, and increased to 2.1% to 5.2% (midpoint 3.7%) within two years.[90] For modeling, we assume that VBID will increase

pharmaceutical demand by 3.7% among patients participating in VBID pharmacy plans which will in turn increases demand for pharmacy-related occupations by this level.

2. **Diagnostic services occupations**: provided by medical and clinical laboratory technologists and technicians, and diagnostic imaging services provided by diagnostic medical sonographers, nuclear medicine technologists, and radiologic technologists. The literature suggests that VBID does cause marginal changes in utilization of diagnostic services to discourage low value services and encourage high value services, but the net impact on demand for diagnostic services occupations is likely to be small.[113,114] [113,114]
3. **Physical therapy (PT)**: VBID has been applied to physical therapy, and a retrospective analysis of medical claims studied the impact of a Geisinger Health Plan initiative aimed at patients with back pain. Geisinger preauthorized patients to receive a "PT bundle" of up to five PT visits for a single one-time copay.[115] Among patients with back pain, PT visits increased by 74% while ED visits declined by 11% over the subsequent 17 months. [115] Among patients with back pain, PT visits increased by 74% while ED visits declined by 11% over the subsequent 17 months. Gellhorn's study in 2012 evaluated the impact of early PT visits for acute lower back pain (LBP).[116] Patients receiving PT within 30 days after initial primary care physician visit for LBP had a lower risk of subsequent surgery or epidural steroid injection, compared to patients receiving PT after 90 days. [116] Patients receiving PT within 30 days after initial primary care physician visit for LBP had a lower risk of subsequent surgery or epidural steroid injection, compared to patients receiving PT after 90 days. In addition, the use of frequent office visits was significantly lower among early PT patients versus those who received PT late. A second study by Fritz also evaluated the effect of early PT visits with similar results.[117] Patients who visited a PT provider within 14 days of primary care consultation showed lower subsequent health care utilization, including imaging, surgery, spine injections, and opioid medications. A second study by Fritz also evaluated the effect of early PT visits with similar results.[117] Patients who visited a PT provider within 14 days of primary care consultation showed lower subsequent health care utilization, including imaging, surgery, spine injections, and opioid medications. Although there is a growing body of literature on VBID applied to PT, there is limited information to inform a scenario for workforce demand modeling. The net effect of VBID is likely to increase demand for PT occupations, but the size of this increase is uncertain.

We reviewed the literature on other trends in care delivery as applied to the allied health and other occupations modeled. The following are select findings from this review, but there is little information in the literature to inform scenario parameters for demand modeling.

- **Bundled payments**: We reviewed literature on bundled payments to ascertain whether there is evidence of changes in services utilization or demand for providers. An evaluation of Medicare claims from 2013-2015 found no statistically significant changes in length of stay, ED use, or readmission after hospital discharge.[82]
- **Non- pharmacological alternatives to pain management**: Studies sponsored by AHRQ suggest the potential for chiropractic care as an alternative to traditional medicine-based therapies to relieve pain associated with some medical conditions.[118,119] The drive to find non-pharmacological alternatives to pain management in part reflects efforts to combat the epidemic of opioid addiction, but these efforts predate the opioid crisis.[120,121] A report from the National Academies of Science, Engineering and Medicine concluded that the heavy burden of pain on human lives, dollars, and social consequences should make this far-reaching issue a national priority.[122] A report summarizing a 2014 meeting of the Association of Chiropractic Colleges Educational Conference examined the contribution of chiropractic care to the changing health care landscape. The report emphasized how well-suited chiropractic services are for the patient-centered medical home and accountable care organizations models.[123] Chiropractic care can be cost-prohibitive because many insurance companies do not cover these services. Some states Medicaid programs are considering increased coverage for chiropractic care for adults, which would tie into national efforts to combat the opioid crisis. National efforts to use non-pharmacological alternatives for pain relief could increase demand for chiropractors, but the magnitude of this increase is unknown.
- **Clinical decision support/ health information exchange**: Information systems or electronic health records that provide clinical decision support have the potential to reduce low-value care or prevent redundant or duplicative testing. Clinical decision support systems also could potentially encourage greater use of high-value care and screening or diagnostic procedures. A systematic review of interventions aimed at reducing use of low-value health services documents interventions outcomes; however, the studies focus on specific services or pharmaceuticals viewed as low value which provides limited use to inform a scenario modeling the workforce demand implications.[124] Likewise, a health information exchange involves sharing electronic information on lab results, clinical summaries and medication with the goals to increase efficiency in care delivery, improve patient outcomes, and reduce service use and medical costs. A systematic review of published studies found little evidence that health information exchanges provide value towards achieving these goals.[125]

- **Technology**: Technology is an essential component of many efforts to improve the health care system, and the use of technology in evolution of the healthcare system has some implications for health workforce demand. Three-dimensional visualization technology has the potential to reduce time required for surgical procedures thus improving efficiency, which in turn could reduce demand for the number of health workers needed to support care delivery.[126] Digital health technologies have the potential to improve how care is delivered. Examples include trackable pill technologies to improve patient medication adherence[127], track health outcomes[128], and provide health coaching.[129] Some technologies could increase demand for certain types of health workers, but the productivity gains could also decrease demand for certain types of providers so the net effect on demand for scenario modeling is uncertain.

Exhibit 19 summarizes the parameters and assumptions used to develop the evolving care delivery system scenario. In summary, while there is an abundance of published studies on care delivery trends and policies influencing how care is used, delivered and financed, there is a paucity of information on how this will affect overall utilization of health care services and demand for the occupations modeled in this report.

Exhibit 19: Evolving Care Delivery System Scenario Parameters and Assumptions

Occupations	Modeling Assumptions	Source
All occupations	Changing demographics and implications for disease prevalence and health care use	Status quo scenario from HWSM simulation
All occupations	Achievement of select population health goals around weight loss; improved control of blood pressure, cholesterol, and A1c levels; and smoking cessation	Disease Prevention Microsimulation Model[22–24,33]
All occupations	All patients will be in managed care plan by 2025; will see changes in care utilization consistent with patterns observed in MEPS for people in managed care versus fee-for-service plans	HWSM simulation
Hospital-based occupations	Assumed gradual 5% reduction in risk-adjusted inpatient days and emergency visits	Numerous studies quantifying the implications of PCMH, team-based care, and other strategies to reduce avoidable hospitalizations and ED use
Select occupations affected by VBID medical and pharmaceutical plan coverage	VBID coverage increases from current level of about 25% to 100% coverage by 2025	Aon Hewitt (2014) for 2014 coverage levels[111]

Occupations	Modeling Assumptions	Source
Pharmacists, pharmacy technicians and pharmacy aides	VBID increases demand for medication by 3.7%, which in turn increase demand for pharmacy occupations by 3.7%	Farley et al. (2012)[90] Look (2015)[112]

VIII. Long Term Services and Support Model Components (updated 2017)

This chapter contains a description of the data, assumptions, and methods used to adapt HWSM to model the sector-specific LTSS workforce. The settings included under LTSS are nursing homes, residential care facilities, home health, hospice, and adult day services centers. Because of data limitations, home health and home-based hospice visits were combined into home care. MEPS data does not distinguish between home health visits associated with chronic care management and visits following hospital discharge for acute conditions.

A. Modeling Supply

HWSM supply projections focus on occupations with high education requirements that creates time lags to train new workers and for which information on future adequacy of supply can help mitigate supply inadequacies. Such occupations usually require a license, and licensing databases often can provide estimates of the current year supply. Licensure data is unavailable for direct care workers, however, and for many health occupations there is no centralized location to obtain licensure data but rather such data would need to be obtained from individual state licensing boards. Therefore, the 2015 American Community Survey is the source for much of the workforce supply data used for the LTSS workforce analysis (Exhibit 20).

The main strengths of the ACS are the availability of occupation code and industry code identifying LTSS setting; data are collected by the U.S. Census Bureau for a large sample of the population in each state; data are collected annually; and there is a wealth of information collected on labor force participation, hours worked, and characteristics of workers—including demographics and education level. There are, however, limitations with ACS to analyze the LTSS workforce:

- Nurse aides, home health aides and psychiatric aides are aggregated in the ACS data into one occupation comprising all aides. Therefore, we supplemented the ACS data with OES data to estimate the portion of aides that were nurse aides, home health aides, and psychiatric aides (Exhibit 21). However, for modeling we categorizing all home health aides under the home health setting.
- Some occupation-industry combinations reported in ACS can be unclear. For example, a home health agency owned by a hospital might be categorized under "hospital" for industry.

Exhibit 20: FTE LTSS Workforce, 2015 American Community Survey

Occupation	Long Term Care Settings				All Health Care Settings
	Total LTC	**Nursing Facilities**	**Residential Care**	**Home Health**	
Direct Care Workers	2,305,300	590,800	543,300	1,171,200	3,207,900
Nursing/Home Health/Psychiatric Aides	1,277,000	523,700	352,800	400,500	1,935,000
Nursing Assistants/Aides	742,500	523,500	159,000	60,000	Unavailable
Home Health Aides	522,700	<100	182,200	340,500	Unavailable
Psychiatric Aides	11,800	200	11,600	<100	Unavailable
Personal Care Aides	1,028,300	67,100	190,500	770,700	1,272,900
Registered Nurses	434,500	250,500	27,000	157,000	2,947,200
Licensed Practical and Licensed Vocational Nurses	361,700	219,400	35,300	107,000	801,000
Healthcare Support Workers, All Other	58,000	40,300	13,200	4,500	152,300
Physical Therapists	43,700	15,100	6,200	22,400	226,000
Occupational Therapists	26,500	13,800	5,500	7,200	98,700
Dietitians and Nutritionists	19,200	13,600	2,200	3,400	85,600
Physical Therapist Assistants	15,800	7,900	3,400	4,500	79,700
Medical Assistants	16,300	4,800	3,700	7,800	515,000
Medical Records and Health Information Technicians	15,800	9,000	1,400	5,400	178,400
Medical and Clinical Laboratory Technicians	15,600	8,600	6,100	900	322,500
Speech-Language Pathologists	13,500	5,100	2,900	5,500	135,900
Occupational Therapy Assistants	8,500	6,300	1,100	1,100	20,300
Respiratory Therapists	3,600	2,300	<100	1,300	99,100
Recreational Therapists	2,900	1,500	700	700	9,700
Healthcare Practitioners and Technical Workers, All Other	3,200	900	500	1,800	141,500
Pharmacists	2,100	1,800	100	200	281,800
Dental Assistants	700	200	200	300	280,100
Dental Hygienists	400	400	<100	<100	143,700
Health Diagnosing and Treating Practitioners, All Other	400	<100	<100	400	22,600
Phlebotomists	300	100	100	100	120,400
Emergency Medical Technicians and Paramedics	400	100	200	100	238,700
Pharmacy Aides	200	100	<100	100	41,000
Total	**3,348,600**	**1,192,600**	**653,100**	**1,502,900**	**10,149,100**

Source: 2015 American Community Survey. Notes: Estimates of full time equivalents were calculated by dividing each person's reported weekly hours worked by 40 hours. ACS combines nursing aides, home health aides and psychiatric aides into one labor category. For this analysis we divided these workers into their own occupations using the workforce distribution from the Occupational Employment Statistics (Exhibit 21) but categorizing all home health aides under the home health setting.

Exhibit 21: LTSS Workforce Jobs, 2015 Occupational Employment Statistics

Occupation	Long Term Care Settings				All Health Care Settings
	Total LTC	Nursing Facilities	Residential Care	Home Health	
Nursing Assistants/Aides	868,300	612,120	185,970	70,210	1,313,690
Home Health Aides	611,130	25,370	200,320	385,440	783,640
Registered Nurses	375,110	154,060	47,460	173,590	2,413,090
Licensed Practical and Licensed Vocational Nurses	355,870	212,980	60,030	82,860	600,850
Physical Therapists	40,850	13,220	1,930	25,700	193,900
Occupational Therapists	24,210	11,420	2,010	10,780	93,970
Medical Records and Health Information Technicians	19,880	11,970	2,700	5,210	143,610
Physical Therapist Assistants	17,950	9,370	1,120	7,460	78,550
Medical Assistants	16,200	5,980	8,800	1,420	573,210
Psychiatric Aides	13,760	240	13,520	-	49,440
Speech-Language Pathologists	12,380	5,770	1,270	5,340	64,930
Dietetic Technicians	10,880	7,940	2,850	90	24,900
Occupational Therapy Assistants	9,810	6,740	850	2,220	32,380
Healthcare Support Workers, All Other	8,320	2,830	4,260	1,230	60,440
Dietitians and Nutritionists	7,490	4,900	1,350	1,240	40,360
Orderlies	7,450	5,510	1,700	240	48,750
Respiratory Therapists	7,100	5,010	450	1,640	112,000
Nurse Practitioners	6,060	1,470	1,200	3,390	124,280
Psychiatric Technicians	5,760	-	5,760	-	46,850
Recreational Therapists	5,480	3,410	1,950	120	14,010
Physical Therapist Aides	4,120	3,130	490	500	48,730
Pharmacy Technicians	2,600	400	300	1,900	74,880
Pharmacists	2,210	340	180	1,690	85,060
Occupational Therapy Aides	1,530	1,190	230	110	6,970
Healthcare Practitioners and Technical Workers, All Other	1,500	730	350	420	26,320
Medical and Clinical Laboratory Technicians	1,330	300	640	390	136,200
Therapists, All Other	1,090	110	560	420	8,800
Family and General Practitioners	1,050	40	70	940	117,160
Psychiatrists	910	-	860	50	20,530
Physicians and Surgeons, All Other	750	140	80	530	270,130
Medical Equipment Preparers	730	50	10	670	47,190
Health Technologists and Technicians, All Other	470	60	70	340	94,600
Respiratory Therapy Technicians	380	230	10	140	9,320
Medical and Clinical Laboratory Technologists	320	-	210	110	144,920
Internists, General	300	50	30	220	47,390
Physician Assistants	250	50	80	120	89,580
Exercise Physiologists	220	50	170	-	5,720
Medical Transcriptionists	210	-	80	130	38,640
Radiologic Technologists	200	60	30	110	185,900
Dental Hygienists	150	70	-	80	195,410
Health Diagnosing and Treating Practitioners, All Other	150	-	-	150	17,330
Phlebotomists	140	100	40	-	113,610
Massage Therapists	110	90	20	-	33,720
Dental Assistants	90	-	60	30	307,570
Occupational Health and Safety Specialists	80	40	40	-	4,520
Diagnostic Medical Sonographers	60	60	-	-	60,380
Dentists, General	60	-	60	-	97,060
Emergency Medical Technicians and Paramedics	50	50	-	-	160,330
Pharmacy Aides	50	-	-	50	4,550
Orthotists and Prosthetists	50	-	-	50	2,190
Pediatricians, General	40	-	40	-	28,130

Source: *2015 Occupational Employment Statistics*. Note: Estimates based on employer surveys and counts do not distinguish between full time and part time staff. http://www.bls.gov/oes/current/oes311011.htm. Adult day care is not an industry category in OES.

Supply modeling for several occupations that work in LTSS settings is described elsewhere in this report—including RNs and LPNs (discussed in Chapter IX); behavioral health providers (discussed in Chapter V); and physicians, APNs and PAs (discussed in Chapter X).

While demand for these occupations is modeled by care delivery setting, supply is not. However, to the extent that comparisons of supply and demand for these occupations helps inform overall adequacy of future supply, one can draw conclusions about the implications for LTSS (which tends to pay lower compensation relative to acute care settings that might employ these health professionals). That is, if the overall supply of nurses is projected to be more than adequate to meet demand for services across the health care sector, then within a particular employment sector such as nursing homes there is a greater likelihood that supply will be adequate (as compared to a situation where there were projections of a system-wide occupation shortage).

Modeling future supply of direct care workers is challenging for the following reasons:

- There are low barriers to entry into the occupation, with states having either no formal training requirements or minimal requirements. Hence, there is little information on the numbers of people entering this occupation each year.
- Given the low barriers to entry into the occupation, there are few barriers to leaving the profession. Unlike occupations such as physicians with lengthy and expensive training that reduces the likelihood a person will change occupations, aides are likely sensitive to earnings and can move in and out of the direct care workforce based on how earnings as a direct care worker compare to earnings from other occupations. Hence, the direct care workforce experiences high rates of turnover. Previous research suggests that wages of direct care workers are most sensitive to higher minimum wage, lower unemployment rate and higher rate of overall Medicaid long-term care spending.[130]

Still, analysis of ACS provides some insights on the potential future size of aide supply. Direct care workers are disproportionately female and minority (Exhibit 22). There are an estimated 2.6 million individuals working as a direct care worker in a LTSS role, equivalent to approximately 2.3 million FTEs (reflecting that some work part time). Together these FTEs represent 1.4% of the employed workforce in the U.S. in 2015. Only 0.2% of employed white, non-Hispanic males worked as a LTSS direct care worker, while 6.2% of black females worked as a direct care worker.

Exhibit 22: Aide Employment by Race-ethnicity and Sex, 2015

	Employed Aides	Total National Employed	Percent of Employed who are Aides
Female	**2,015,100**	**75,428,000**	**2.7%**
White, non-Hispanic	882,400	48,195,000	1.8%
Black, non-Hispanic	621,100	9,942,000	6.2%
Other, non-Hispanic	163,600	6,096,000	2.7%
Hispanic	348,000	11,195,000	3.1%
Male	**290,200**	**84,398,000**	**0.3%**
White, non-Hispanic	126,500	54,656,000	0.2%
Black, non-Hispanic	83,400	8,656,000	1.0%
Other, non-Hispanic	39,300	6,504,000	0.6%
Hispanic	41,000	14,582,000	0.3%
Total	**2,305,300**	**159,826,000**	**1.4%**

Source: 2015 American Community Survey. The "Other" category combines all remaining racial or ethnic groups which are not modeled separately due to small sample size in many of the databases analyzed (e.g., the Medical Expenditure Panel Survey for analyzing health care use patterns). This category includes Native Americans, Alaska Natives, Native Hawaiians and other Pacific Islanders, Asian Americans, Middle Easterners and North Africans, and others who self-identify as other than White, Black, or Hispanic.

Based on national changing demographics, populations with greater propensity to be direct care workers (Hispanics, blacks) are growing more rapidly than populations with lower propensity to be direct care workers (non-Hispanic white and other races). If the propensity to be a direct care worker within each demographic group were unchanged, this suggests about 14% growth in direct care workforce supply between 2015 and 2030 (rising from 2.3 million FTEs to over 2.6 million FTEs). While such supply growth likely will be insufficient to keep up with projected growth in demand for services, there is great potential to rapidly grow the direct care workforce simply by increasing wages.

B. Modeling Demand

The projected demand for LTSS and workforce was derived from the common model estimated on the baseline population and health care usage as outlined in Chapter III. HWSM already models the demand of many occupations relevant to LTSS (e.g., RNs, LPNs, nurse and home health aides), and these projections have been refined for modeling LTSS settings. Previous efforts to model LTSS settings used simplifying assumptions—such as modeling growth in demand for nursing homes and residential care services strictly as a function of an aging population (specifically, the population age 75 and older). Areas of enhancement to demand modeling include refining the relationship between patient characteristics and economic factors and use of LTSS services, adding the adult day care setting, including estimates for unpaid care demand, adding occupations to the model, and refining the scenarios modeled (taking into account possible changes in care use and delivery patterns).

The population file used for modeling demand was updated to include representative samples of the community-based, residential care-based and nursing home-based populations as noted in Chapter III. To construct the population file, historically a matching algorithm was used to combine the latest data from ACS, BRFSS, and NNHS. Starting with this analysis of the LTSS workforce, a representative sample of the population residing in a residential care facility was added (whereas previously this population was modeled as living in the community). We identified beneficiaries in the MCBS who reside in a residential care facility and used this sample to construct a representative sample of the population in each state living in residential care. Likewise, we used CMS's 2015 Nursing Home MDS to develop a representative sample of the population in nursing homes. The result was a population file with a representative sample of the population in each state who might use community-based services including home health and adult day services, a representative sample of the population living in residential care facilities, and a representative sample for the population in a nursing home.

Baseline demand for LTSS was projected under the assumption that recent patterns of care use and delivery would remain unchanged within each demographic group defined by age, sex, and race-ethnicity. Predicted probabilities were applied to the simulated micro-data set for future years to obtain projected service use specific to the settings that employ long-term care occupations.

For modeling demand for adult day service center, probabilities were assigned to specific population cohorts defined by age group and these probabilities were applied to the population database. The target population was identified as people living in communities with any cognitive difficulty. These probabilities based on age-distribution of adult day service center patients were obtained from the National Study of Long-Term Care Providers.[131] Approximately 4,800 adult day service centers reported employing around 23,100 FTE nurses and social workers.[132] Among the workforce modeled for the LTSS projections include an estimated 13,700 nurse aides, 4,100 RNs, and 2,500 LPNs working in adult day service centers.

The LTSS component of HWSM currently models demand for approximately 30 professions defined by occupation and medical specialty (for physicians). Many of these professions employ few workers in LTSS. HWSM used provider staffing patterns to convert demand for LTSS into demand for the relevant occupations. These staffing patterns were applied to the constructed population database to generate baseline state and national projections by LTSS setting and occupation. To construct the staffing ratios for home health, nursing homes and residential care facilities (Exhibit 23), we divided the workload driver for each setting by estimates of FTE providers (Exhibit 20) from the 2015 ACS.

Exhibit 23: Ratio of Annual Care Utilization to FTEs, 2015

Occupation	Home Health	Nursing Home	Residential Care	Adult Day Service Centers
Personal Care Aides	29*	20	3.6	NA
Nursing Aide	371*	2.5	4.4	21
Home Health Aide	65*	NA	3.8	NA
Registered Nurses	142*	5.2	26	69
Licensed Practical and Licensed Vocational Nurses	208*	6.0	20	113
Healthcare Support Workers, All Other	4,920	33	53	NA
Physical Therapists	995*	87	111	NA
Occupational Therapists	757*	95	125	NA
Dietitians and Nutritionists	6,525	96	311	NA
Medical Assistants	2,852	271	186	NA
Medical Records and Health Information Technicians	4,137	146	484	NA
Physical Therapist Assistants	2,094*	166	204	NA
Medical and Clinical Laboratory Technicians	10,513	153	114	NA
Speech-Language Pathologists	4,045	254	243	NA
Psychiatric Aide	NA	6,391	60	NA
Occupational Therapy Assistants	502*	209	621	NA
Respiratory Therapists	16,818	566	NA	NA
Healthcare Practitioners and Technical Workers, All Other	12,675	1,413	1,479	NA
Recreational Therapists	31,341	891	994	NA
Pharmacists	123,797	739	13,599	NA
Annual utilization	21.8 million home health visits	1.3 million residents	694,000 residents	282,000 patient days

Note: Annual home health visits varies by occupation. * indicates staffing ratio is based on home health visits specific to the occupation as calculated using MEPS; all other occupations use ratios based on total annual home health visits (regardless of type of visit). NA indicates occupation is not applicable to the employment setting.

In addition to developing prediction equations for paid care, we analyzed NHATS to develop prediction equations of how much unpaid care is provided (i.e., informal care giver such as a family member or friend). The purpose of this analysis was to determine if trends affecting future supply and demand for unpaid care might affect future demand for paid care—and in particular future demand for direct care workers. The regression estimates from NHATS were applied to the non-nursing home population age 65 and older in the population database to model total hours of unpaid care.

First, using logistic regression we analyzed the propensity of individuals to use paid and unpaid care (Exhibit 24). Older age and presence of activities of daily living limitations were associated with greater odds of receiving both paid and unpaid care.

Second, using a negative binomial regression model we analyzed total paid and unpaid care hours received per week for those individuals who reported receiving at least one hour of care (Exhibit 25). FTE demand for unpaid care assumed 1 FTE equal to 40 hours of unpaid care. Older age and presence of select ADL limitations were associated with greater number of paid and unpaid hours per week of care received.

Exhibit 24: Whether a Person Uses Paid and Unpaid Care

	Characteristic	**Use of Paid Care (Odds Ratios)**	**Use of Unpaid Care (Odds Ratios)**
Race-Ethnicity	Non-Hispanic white	1.00	1.00
	Non-Hispanic black	1.19	1.17*
	Non-Hispanic other race	0.55**	0.86
	Hispanic	1.69**	1.16
	Male	1.07	1.51**
Age	65-69 years	1.00	1.00
	70-74 years	0.89	0.70**
	75-79 years	0.71**	0.93
	80-84 years	1.19	0.98
	85-89 years	1.41**	1.24**
	90+ years	1.63**	1.46**
Difficulty/Health Indicators	History of heart attack	1. 17	0.94
	History of stroke	1. 16	1.00
	Hearing difficulty	1. 07	1.02
	Vision difficulty	1. 49**	1.03
	Walking difficulty	2. 24**	1.30**
	Self-care difficulty	4.83**	1.67**

Note: Logistic regression modeling use of paid care (yes/no) and unpaid care (yes/no). Statistically significant at the 0.01 (**) or 0.05 (*) level. n = 7,385.

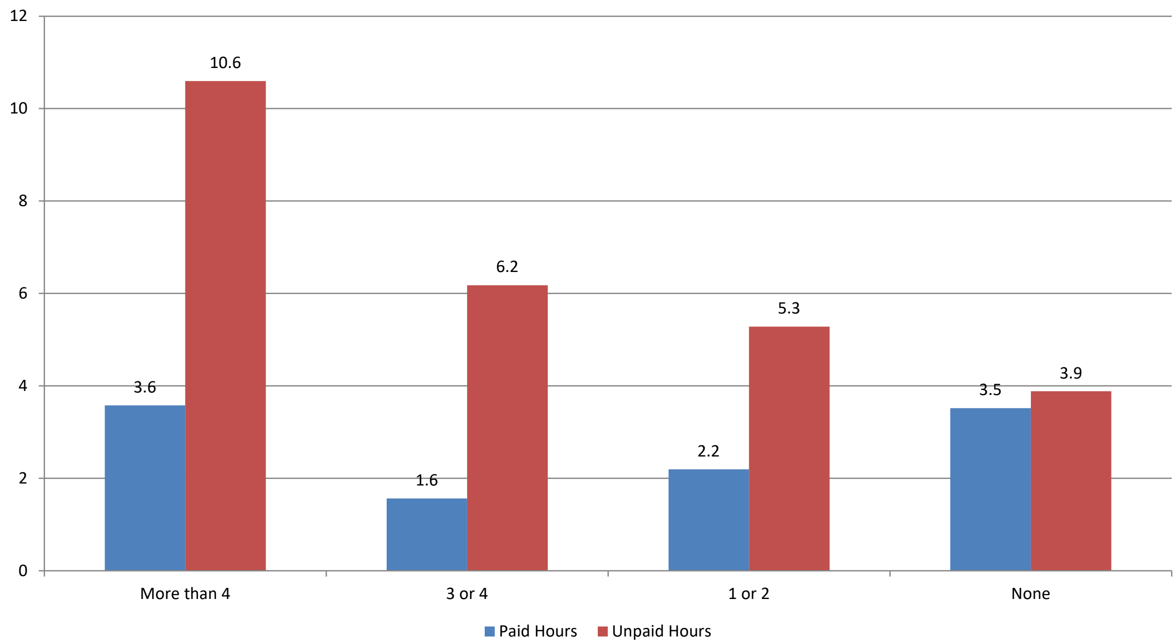
Exhibit 25: Weekly Hours of Paid and Unpaid Care Received

Characteristic		Paid Hours/Week (Rate Ratio)	Unpaid Hours/Week (Rate Ratio)
Race-Ethnicity	Non-Hispanic white	1.00	1.00
	Non-Hispanic black	1.08	1.64**
	Non-Hispanic other race	1.65*	1.59**
	Hispanic	1.37	1.43**
	Male	0.97	1.49**
Age	65-69 years	1.00	1.00
	70-74 years	1.01	0.80
	75-79 years	1.20	1.10
	80-84 years	1.30	1.09
	85-89 years	1.62*	1.31*
	90+ years	1.86**	1.12
Difficulty/Health Indicators	History of heart attack	0.91	0.95
	History of stroke	1.11	1.43**
	Hearing difficulty	1.03	1.06
	Vision difficulty	0.88	1.20
	Walking difficulty	1.74**	1.66**
	Self-care difficulty	1.66**	1.30**

Note: Negative binomial regression modeling weekly hours of paid care and unpaid care. Statistically significant at the 0.01 (**) or 0.05 (*) level. n = 509 for paid care; n=1,242 for unpaid care.

The focus of this work was modeling growth in demand for unpaid hours of care, though projections of growth in paid hours of care were consistent with projected growth in demand for personal care aides and home health aides. We explored whether the trend to decreasing family size might affect future supply of unpaid care and the implications for demand for paid care.[133] Analysis of NHATS found that the smaller family size is correlated with greater weekly hours of paid care and fewer weekly hours of unpaid care. However, the overall impact of decreasing family size is relatively small and does not appear to substantially affect demand for paid care workers.

Exhibit 26: Average Weekly Hours of Paid and Unpaid Care, by Number of Children



The status quo scenario for modeling demand assumes prevalence rates of functional impairments among people of different age, sex and race/ethnicity will remain constant over time. It assumes that recent patterns of care use and delivery will remain unchanged, but incorporates population growth and aging. Demand projections were developed at the state level and then aggregated to obtain the national projections. The state-level projections take into consideration geographic variation in health risk factors and demographics.

Demand was modeled under a scenario focusing on forecasting population health status and to capture trends and expectations in care use and delivery. This Population Health scenario is described in more detail in Chapter IX, but assumes that the nation achieves sustained reductions in excess body weight; smoking cessation; and improving uncontrolled hypertension, hypercholesterolemia, and hemoglobin A1C levels. Such a scenario might be achieved under a medical home model, and is based on national priorities to improve access to preventive care. Trends that might help achieve such a scenario include: (a) increased organizational and policy commitment to population health as illustrated by health care reform, ACO-related quality metrics targeted at population health, and payment reform; (b) greater assumption of risk by providers; and (c) better infrastructure to manage population health.

IX. The Nursing Model Components (updated 2016)

A. Modeling Supply

Estimating Base Year Nurse Supply

For most states, estimates of the current supply of RNs and LPNs came from the pooled 2010-2014 ACS files. Five years of data were combined to increase the sample size to provide stable state-level estimates of the distribution of nurses by education level, age, sex and race/ethnicity (which is a new component added to the supply model). The ACS sample weights from the 5-year file were recalibrated to sum to the state totals of RNs and LPNs in the 2014 ACS. HWSM was designed to use data from state licensure files as data becomes available for use instead of ACS data.

Four states (Georgia, Oregon, South Carolina, and Texas) provided licensure data so for those states the starting supply is based on licensure data instead of the ACS.[a] Criteria for including nurses in the licensure files are that the nurse was licensed and active in nursing in the state being modeled. The main difference between the licensure files and ACS in terms of defining an active nurse is that with licensure files we could verify the nurse was licensed in the state, whereas with the ACS data licensure was implied by the ACS respondent self-reporting activity status and occupation as a nurse.

The ACS estimates extrapolated to 2015 averaged 5-8% higher for RNs-LPNs compared to estimates from the 2015 licensure files, though the differences varied by state-occupation combinations.[b] A comparison of ACS and licensure files for these four states suggests that (1)

[a] These state licensure data were 2015 data, while the ACS data was 2014 data. Consequently, to obtain 2014 estimates for these states we projected backwards based on projected graduates and attrition from 2014 to 2015.

[b] For example, ACS estimates for RNs in Georgia and South Carolina appear to be similar to estimates from state licensure files, while for Oregon the ACS estimate is smaller and for Texas the ACS estimate is larger. For LPNs, the Georgia and Texas estimates are relatively consistent with estimates from state licensure files, while for Oregon and South Carolina the ACS estimates are much larger in percentage terms than are estimates from state licensure files.

Source	GA	OR	SC	TX	4-State Total
RNs: 2015 projected from 2014 ACS	85,600	33,700	47,900	222,300	389,400
RNs: 2015 Licensure files	84,600	37,600	49,400	200,700	372,200
Difference (ACS-Licensure)	1,000	(3,900)	(1,500)	21,600	17,200
% Difference	1%	-10%	-3%	11%	5%
LPNs: 2015 projected from 2014 ACS	29,800	4,400	12,900	78,200	125,400
LPNs: 2015 Licensure files	27,900	3,400	8,600	76,500	116,400
Difference (ACS-Licensure)	1,900	1,000	4,300	1,700	9,000
% Difference	7%	29%	50%	2%	8%

the RN estimates from the ACS appear to be more consistent with licensure files than are the LPN estimates from ACS—likely reflecting that LPN sample size is smaller in ACS compared to sample size for RNs; (2) if at the national level ACS overestimates FTE supply of nurses then the estimates of national demand based on ACS also might be overestimated by a similar percentage; and (3) information from additional states would help determine to what extent the ACS accurately reflects estimates of supply from state licensure files.

Modeling New Entrants to the Nursing Workforce

New entrants reflect nurses entering the workforce for the first time upon completion of a nursing program, as well as individuals who migrate mid-career from one geographic area to another (discussed later). HWSM used first time, U.S.-educated candidates taking the National Council Licensure Examination (NCLEX) as the starting point for estimating the number of new entrants to the nursing workforce. In 2014, there were 157,882 first-time U.S.-educated takers of the NCLEX-RN.[a] Of these, 70,857 nurses had completed a baccalaureate degree and 87,025 had completed a diploma or an associate degree.[134] There were 55,489 first time takers of NCLEX-LPN in 2014. Based on the assumption that nurses who initially fail the NCLEX will retake the test at least twice, we assumed an eventual pass rate of 96% of RNs trained at the associate level, 98% of RN trained at the baccalaureate level, and 95% of LPNs, and that these nurses will enter the workforce.

For modeling future supply under a status quo scenario, HWSM assumed that annually the number of nurses passing the NCLEX includes 69,440 RNs at the baccalaureate level, 83,540 RNs at the associate or diploma level, and 52,720 LPNs. The new entrant statistics for RNs include the estimated 16,000 LPNs who further their education and become RNs each year. Alternative supply scenarios modeled include training 10% more or 10% fewer nurses, relative to current numbers, to illustrate the sensitivity of supply projections to the number of nurses being educated each year.[b]

The National League of Nursing survey of students enrolled in entry level nursing programs in 2014 suggests that 91% of LPNs are female, 86% of RNs in associate or diploma programs are female, and 85% of RNs in baccalaureate programs are female.[135] Estimates of the age distribution for new nurses come from analysis of the 2008 National Sample Survey of Registered Nurses (Exhibit 7). Limited data is available on the age distribution of new LPNs, but National League for Nursing data from 2008-2009 suggests that the age distribution fore LPNs is

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[a] Foreign educated NCLEX takers are excluded from this analysis because there is no evidence that employers currently are relying on foreign educated nurses to fill nursing vacancies. Many foreign educated nurses take NCLEX but do not come to the U.S.

[b] Additional scenarios modeled include ±5% change in nurse productivity levels, and ±2 years earlier or delayed retirement.

similar to the age distributions for Diploma and Associated Degree RNs.[136] Hence, for modeling we use the age distribution of Diploma and Associated Degree RNs as a proxy for the age distribution of LPNs. The race and ethnic distribution of new nurses varies widely by state, and we use the race/ethnicity distribution of nurses age 30 or younger in the 2010-2014 ACS as a proxy for the age distribution of new nurses (Exhibit 28).

Exhibit 27: Age Distribution of New RNs and LPNs

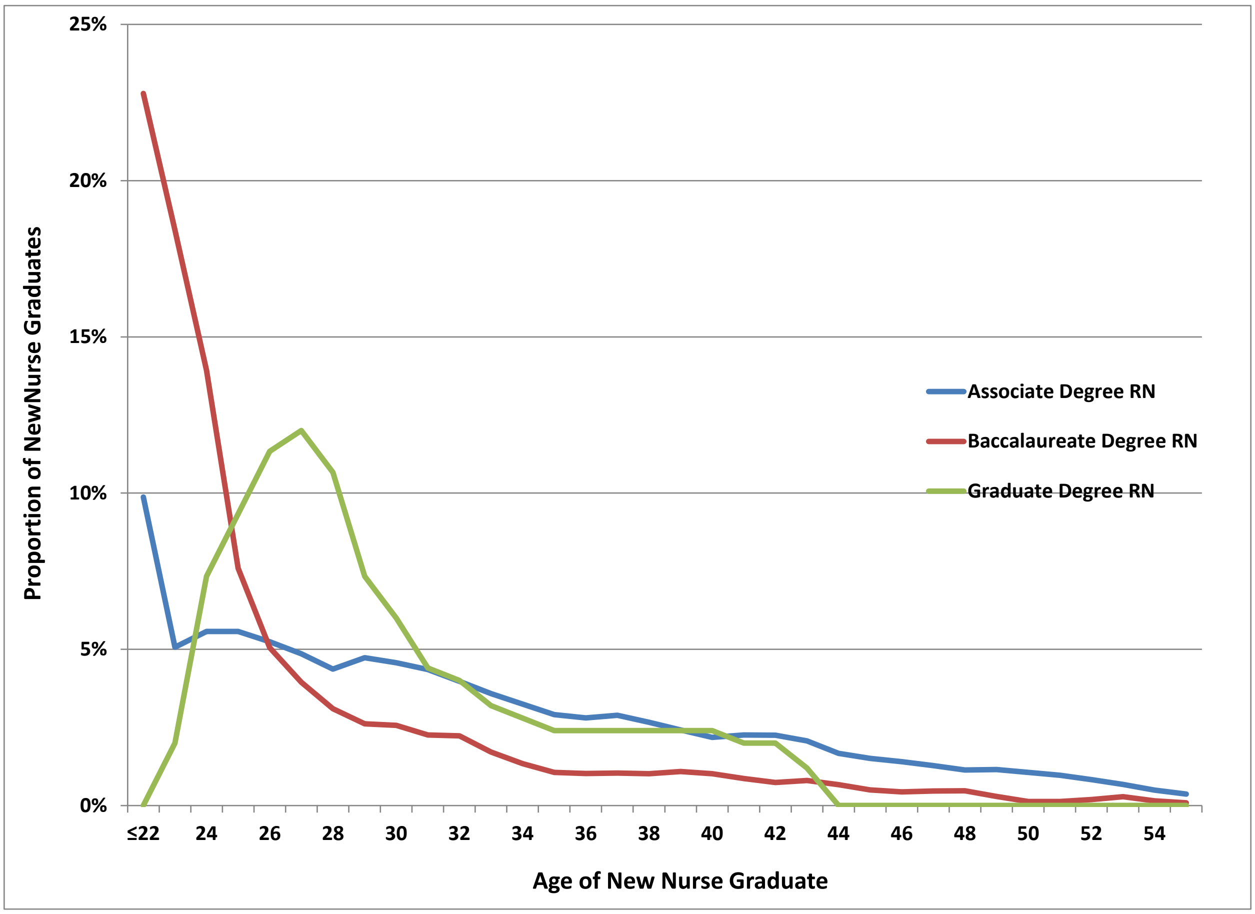

Exhibit 28: Race and Ethnicity Distribution of New RNs and LPNs by State (%)

	Registered Nurses				Licensed Practical Nurses			
	Non-Hispanic				Non-Hispanic			
State	WHITE	BLACK	OTHER[a]	HISPANIC	WHITE	BLACK	OTHER[a]	HISPANIC
AK	95	0	5	0	71	0	29	0
AL	85	11	2	3	64	33	3	0
AR	83	12	1	4	70	20	7	3
AZ	70	3	9	18	59	4	12	26
CA	38	3	39	21	23	9	34	34
CO	83	2	6	9	52	13	6	28
CT	75	11	7	6	51	26	8	14
DC	56	24	10	11	17	83	0	0
DE	74	19	3	4	63	29	8	0
FL	53	18	10	19	43	31	5	21
GA	68	23	5	4	50	45	2	3
HI	29	4	59	8	41	0	49	10
IA	97	1	0	2	90	6	2	2
ID	94	0	2	4	89	0	0	11
IL	73	5	14	8	49	28	12	11
IN	90	4	3	3	76	14	2	8
KS	86	7	4	4	71	9	9	12
KY	92	5	2	0	86	11	3	0
LA	71	22	3	3	52	44	2	2
MA	78	8	9	5	70	15	7	9
MD	58	23	14	5	46	47	2	4
ME	98	0	2	0	98	0	2	0
MI	89	5	4	2	65	29	4	2
MN	89	4	4	2	81	9	8	3
MO	87	9	3	2	71	23	3	2
MS	76	22	1	1	47	46	4	4
MT	97	0	3	0	83	0	17	0
NC	83	11	4	3	68	23	5	3
ND	92	2	5	1	70	0	30	0
NE	92	3	2	3	90	4	3	4
NH	92	4	3	0	73	3	14	9
NJ	59	12	19	10	37	39	11	14
NM	49	1	5	45	21	2	21	56
NV	47	9	37	7	64	3	16	16
NY	59	18	15	8	52	33	5	10
OH	90	7	2	2	68	28	1	3
OK	74	8	14	4	62	15	21	3
OR	85	0	10	5	65	0	24	11
PA	87	6	4	2	74	18	3	5
RI	81	3	14	1	43	10	13	34
SC	73	20	6	2	63	35	1	1
SD	95	1	4	0	98	0	0	2
TN	87	9	2	2	82	13	2	3
TX	56	11	11	22	42	16	5	37
UT	93	1	4	2	91	0	5	5
VA	75	13	8	4	52	35	6	7
VT	100	0	0	0	88	0	10	2
WA	75	5	16	4	70	2	17	11
WI	91	2	4	3	86	6	4	4
WV	96	1	2	0	96	4	0	0
WY	95	0	1	4	82	0	7	12
US	73	9	10	8	57	21	9	13

Notes: Analysis of race and ethnic identify of nurses age 30 or under in the 2010-2014 combined files of the American Community Survey. [a] "Other" category includes Asian and Pacific Islander and American Indian.

Modeling Nurse Workforce Participation

Nurses might temporarily leave the labor force due to family, education, economic or other considerations. Permanent departure from the labor force might be due to retirement, career change to another occupation, or death—or when modeling workforce for a geographic area might be the result of emigration (moving away from that geographic location to work elsewhere). This section describes permanent attrition from the workforce modeling, labor force participation, and weekly hours worked. Modeled hourly wage—which is one input used to model labor force participation and hours worked patterns—also is described.

Attrition Patterns

In this section, we describe analyses and assumptions regarding nurses who permanently leave the nursing workforce—which differs from temporary departures such as for child rearing, illness, or other reasons where the nurse intends to eventually return to employment.

We modeled a small amount of attrition each year for nurses under age 50. The preliminary RN supply projections assumed that about 97% of RNs taking the NCLEX exam for the first time would eventually pass and enter the workforce. We then modeled labor force participation rates using the ACS, and estimated that about 92-95% of RNs would be active in the workforce through age 50 depending on age. After age 50 we model attrition from the workforce as nurses age.

The challenge with ACS data is that if an RN has been out of the workforce for five or more years then ACS does not collect occupation data. However, if the RN remains in the workforce but in a non-nursing position then their occupation will not indicate RN but indicate the current occupation. While our starting supply of RNs will be accurate, our labor force participation rates will not reflect some younger RNs permanently leaving nursing.

HRSA's 2008 Sample Survey of RNs indicates that a small percentage of RNs under age 50 intends to leave the workforce, and a small percentage of recent graduates are not employed in nursing.[137] However, this snapshot for 2008 was in the middle of a national recession. Also, of nurses not working in nursing, many plan to return to nursing. One challenge with the survey data is that when a nurse indicates an intention to leave nursing in the next 3 years (i.e., the question asked) it is unclear whether the intention is to permanently or temporarily leave nursing. The survey indicates that for nurses under age 50 who are not working in nursing approximately 57.5% have been out of nursing for 0-4 years (so presumably most of these nurses are represented in the ACS unless they are working in a different occupation so their occupation code changed). An estimated 42.5% of nurses who have left nursing have been out of nursing for five or more years so these nurses would not be represented in ACS as a nurse. Therefore, the ACS likely understates the number of trained nurses who are not active in nursing by a few percentage points. Some nurses who indicate they are not in nursing are in other health occupation or government jobs, so it is possible that these nurses still are working in a role that requires a nursing background or degree even though the nurse is not practicing in a traditional nursing role.

According to the 2008 survey, by age 30-34 approximately 8.7% of nurses are not employed in nursing, growing to about 10% from age 40-49.[137] Analysis of the ACS indicates about 92-95% not employed in nursing (with the percentage not employed varying by age). Based on the data in Figure 3-4 and Figure 3-24 of the 2008 survey report we make the following assumptions:

From when the nurse initially enters the workforce through age 39 each year there is a 0.33% probability of leaving the workforce each year. For example, if a nurse enters the workforce at age 25 then by age 39 she has a cumulative 3.3% probability of having permanently left nursing (on top of an approximately 5% probability of being out of the workforce).
Between age 40 and 49 there is an estimated 0.42% probability of leaving the workforce each year (based on our calculations). By age 49 a nurse who entered the workforce at age 25 has an 8.8% cumulative probability of having permanently left the workforce (on top of an approximately 5% probability of being inactive).

In summary, the modeling assumptions are that approximately 3% of nurses who graduate from a nursing program do not pass the NCLEX and enter the workforce; there is an 8.8% probability of leaving nursing by age 49 and a 92-95% employment rate for those in nursing through age 49; and from age 50 and older the nurses have a probability of permanently leaving the workforce that increases with age (as described later). For each 100 nurses graduated from a nursing program at age 25, we calculate by age 49 approximately 84 of these nurses would be working in nursing (with 3 never entering the workforce, 8 having left nursing altogether, and 5 currently out of the workforce).

Multiple approaches have been explored and used to estimate nurse attrition patterns. Prior to 2016, ACS-derived labor force participation rates by age and sex for RNs age 50 and younger were used. For RNs over age 50 labor force participation rates for college educated men and women over age 50 were used as a proxy for labor force participation rates for male and female RNs over age 50 with a similar education level (i.e., with an associate degree, a baccalaureate degree, or a graduate degree). As noted above, ACS does not capture occupation for individuals out of the workforce for five years or more.

Refined estimates of nurse attrition patterns are used in the updated supply projections based on licensure data from Oregon, South Carolina and Texas (Exhibit 29). Multiple years of licensure data (2010-2015) were analyzed. These licensure data do not contain individual identifiers to link nurses across years. Therefore, we compared the age distribution of active RNs in one year to the expected age distribution in a subsequent year if all RNs active in prior year had remained active. The gap reflects net attrition from the workforce (including mortality, retirement and net migration out of the state).

The Oregon data reflected a survey question about intention to retire within the next three years. Based on informal communications with staff from the Oregon Center for Nursing, approximately a quarter of all nurses who in 2010 had expressed an intention to retire within the next three years were still in the workforce in 2014. Therefore, we adjusted the estimated attrition patterns based on intention to retire to reflect Oregon's previous analysis that intention to retire might overstate actual retirement. Also, we added mortality patterns to the intention to retire patterns to estimate overall attrition rates.

The supply projections are based on the average attrition patterns estimated across the three states. Attrition patterns differ by age and nurse type (RN or LPN), but do not differ by other nurse characteristics. This is an area of ongoing research. Also, the attrition patterns used in the model reflect input from participants in a recent nurse workforce retreat sponsored by HRSA.[a]

For nurses age 70 and older the sample sizes in the state licensure files are small and estimates of attrition patterns fluctuate accordingly. Therefore, we assume that starting at age 70 the annual attrition rate is 50%. In addition, we model that annually approximately 16,000 LPNs become RNs and approximately 16,200 RNs leave the RN workforce each year to become nurse practitioners (reflecting that close to 15% of NPs remain practicing in a traditional RN role).

The approach used for modeling attrition patterns reflects limitations with data sources such as ACS. If a person has been out of the workforce for 5 years or more, then ACS does not collect information on prior occupation. Likewise, if a person left nursing for a career outside of nursing then the ACS captures data on the current occupation but there is no indication of previously having been working in nursing. Hence, estimates of attrition patterns based on ACS can understate true attrition patterns.

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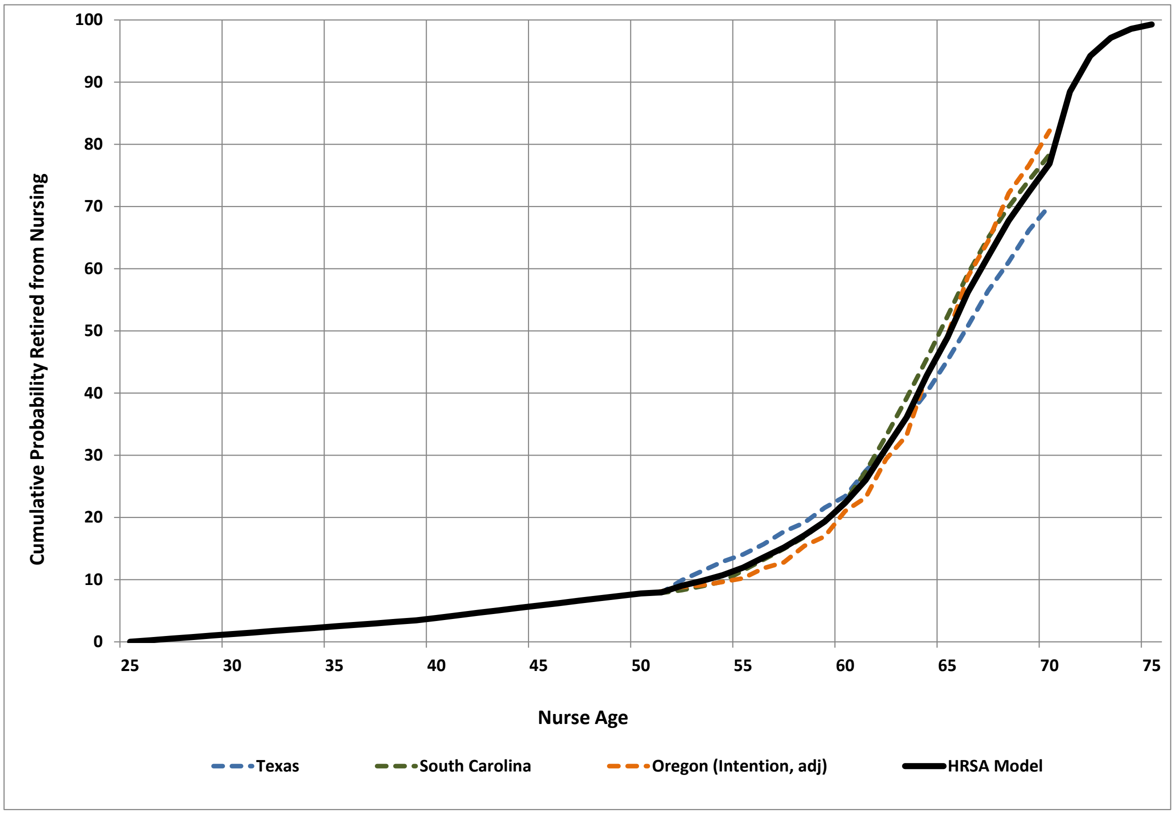
[a] In July 2016, HRSA and the Montana State University Center for Interdisciplinary Health Workforce Studies sponsored a 3-day meeting of nurse workforce researchers to critique alternative approaches to modeling nurse workforce supply and demand and to provide input on HRSA's workforce modeling assumptions, inputs and methods. One outcome of this meeting was to incorporate workforce attrition probabilities among younger nurses, and to adjust estimates of the number of RNs being trained as advanced practices nurses to reflect that some RNs become trained as APNs but still continue to practice in a traditional RN role.

Exhibit 29: RN Estimated Attrition Patterns



Hourly Wages

Earnings potential (modeled in terms of hourly wages) are modeled as a function of nurse characteristics and external factors as summarized in Exhibit 30. The equations to predict hourly wages were estimated separately by nursing occupation using data from the 5-year (2010-2014) ACS for individuals who are currently employed. Hourly wages were calculated by dividing estimated weekly earnings by estimated weekly hours and omitting records where hourly wages were below the 5th percentile of above the 95th percentile (as estimated hourly wages for these omitted records were outside the plausible range). Included as an explanatory variable is state mean hourly wage for that occupation from the OES data, with mean wage varying across states and years. Both occupation mean hourly wage and each person's hourly wage (i.e., the dependent variable in the regression) were adjusted to 2015 dollars using the consumer price index and adjusted to a national average using a state cost-of-living index.[138]

For the nursing occupations modeled, individual wage is highly correlated with occupation mean wage in that state. Wages tend to increase for those early in their career, but rise more slowly above age 35. Male nurses tend to earn higher hourly wages. Wages vary by race/ethnicity. Hourly wages rise with the percentage of the population living in suburban areas. As with many cross-sectional analyses using person-level data, the R-squared values for these equations are low reflecting that these regressions explain only a small portion of cross-sectional variation in hourly wages worked.

Exhibit 30: OLS Regression Coefficients Predicting RN/LPN Hourly Wages

Parameter	RN	LPN
Intercept	-2.67 **	-0.46
Unemployment rate (state, year) [a]	-0.15 **	-0.03
State occupation mean hourly wage [a]	0.85 **	0.84 **
Age 35 to 44 [b]	3.87 **	2.15 **
Age 45 to 54 [b]	5.21 **	2.80 **
Age 55 to 59 [b]	5.79 **	3.41 **
Age 60 to 64 [b]	5.74 **	3.43 **
Age 65 to 69 [b]	4.70 **	3.42 **
Age 70+ [b]	2.07 **	2.58 **
Male [b]	1.18 **	0.62 **
Year 2011 [b]	-0.38 **	-0.46 **
Year 2012 [b]	0.39 **	-0.44 **
Year 2013 [b]	0.14	-0.40
Year 2014 [b]	-0.29 **	-1.72 **
Non-Hispanic black [b]	-0.15	0.60 **
Non-Hispanic other [b]	-0.66 **	0.38 **
Hispanic [b]	1.12 **	-0.82 *
Have nursing baccalaureate degree [b]	2.55 **	NA
Having nursing graduate degree [b]	4.10 **	NA
Percentage of state's population residing in suburban area	0.13 **	0.76 **
Percentage of state's population residing in a rural area	0.01	0.01 **
Sample size	150,504	37,294
R-squared	0.12	0.11

Notes: Statistically significant at the 0.01 (**) or 0.05 (*) level. [a] State mean by year from the Bureau of Labor Statistics. [b] Comparison groups are age <35, female, year=2010, non-Hispanic white, and (for RNs only) associate or diploma as highest educational degree. Odds ratios reflect 100% suburban versus 0%, or 100% rural versus 0%. Source: Analysis of the 2010-2014 files of the American Community Survey.

Hours Worked

Forecasting equations related average hours worked to nurse age, sex, education level, state overall unemployment rate, and average wage in the occupation. Data for all variables came from the ACS with the exception of average wage, which was obtained from the BLS. To convert average hours worked into Full Time Equivalents (FTEs), an assumption needed to be made about the average number of hours worked per week by a full-time nurse. Analysis of the ACS suggests that among nurses working at least 20 hours per week, for both RNs and LPNs the average hours worked per week is 37.3. However, for modeling purposes HRSA is now defining an FTE as 40 hours per week (a measure which can remain constant over time and across health occupations). While workforce projections published before 2017 used different hour estimates to define an FTE, from 2017 onward the decision was to use 40 hours.

Ordinary Least Squares regression coefficients showed that average weekly hours worked declined substantially among older nurses (Exhibit 31). For both RNs and LPNs, weekly hours worked decline rapidly from age 60 onward. On average, male RNs work 2.78 more hours and male LPNs work 1.77 more hours than their female counterparts. Hispanic RNs work 2.28 hours more than non-Hispanic white RNs, RNs with a baccalaureate or graduate degree work 1.43 hours more than RNs with an associate or diploma degree, and RNs and LPNs in states with a larger proportion of the population residing in rural areas[1] tend to work more hours. Hours worked per week by RNs and LPNs rises slightly with the unemployment rate.

Exhibit 31: OLS Regression Coefficients Predicting Weekly Hours Worked for RNs and LPNs

Parameter	Registered Nurses	Licensed Practical Nurses
Intercept	35.15 **	34.44 **
Unemployment rate (state, year) [a]	0.05 *	0.05
Predicted wage	0.01	0.04
Age 35 to 44 [b]	0.26 **	1.85 **
Age 45 to 54 [b]	1.20 **	2.04 **
Age 55 to 59 [b]	0.88 **	1.52 **
Age 60 to 64 [b]	-0.31 **	0.35
Age 65 to 69 [b]	-4.54 **	-4.33 **
Age 70+ [b]	-8.57 **	-7.42 **
Male [b]	2.78 **	1.77 **
Year 2011 [b]	0.14	-0.02
Year 2012 [b]	0.21 *	0.27
Year 2013 [b]	0.30 **	0.17
Year 2014 [b]	0.38 **	0.22
Non-Hispanic black [b]	-0.24 **	1.05 **
Non-Hispanic other [b]	1.56 **	1.16 **
Hispanic [b]	2.28 **	1.04 **
Have nursing baccalaureate degree [b]	1.43 **	NA

Having nursing graduate degree [b]	1.43 **	NA
State's percentage of population residing in a suburban area	0.73	-2.09 *
State's percentage of population residing in a rural area	1.41 **	1.96 **
Sample size	150,504	37,294
R-squared	0.04	0.04

Note: Statistically significant at the 0.01 (**) or 0.05 (*) level. [a] State mean by year from the Bureau of Labor Statistics. [b] Comparison groups are age <35, female, year=2010, non-Hispanic white, and (for RNs only) associate or diploma as highest educational degree. Source: Analysis of the 2010-2014 files of the American Community Survey.

Activity Status

Activity status for nurses is modeled using prediction equations derived from ACS (2010-2014) data. This analysis focused on nurse clinicians under age 50 (as the activity status for clinicians over age 50 is modeled as attrition). The dependent variable was whether the nurse was employed or not employed. The unemployed population is everyone currently now employed but whose most recent employment in the past five years was in nursing. Explanatory variables are the same used to model hours worked. The overall activity rate for RNs and LPNs under age 50 was, respectively 95% and 91%. The odds of being employed vary by nurse demographics—in particular age (Exhibit 32). A higher overall unemployment rate slightly raises the odds of RNs being employed, while higher earnings potential is associated with a slight decrease in the odds that RNs are employed. Interaction terms for sex and age group are included to reflect that labor force participation differences between men and women might differ by age group. To compare male RNs age 35-39 versus female RNs of the same age, one multiplies the odds ratios for male and the male-age interaction. For example, male RNs age 35-39 have twice the odds (0.71*2.81=2.00) of being active in the nursing workforce as do female RNs of the same age. Male RNs age 45-49 have odds of being active in the labor force that are 1.38 times the odds for female RNs of similar age.

Compared to non-Hispanic white nurses, the odds that an RN is active in nursing is 38% higher for Hispanics, 32% higher for non-Hispanic blacks, and 23% higher for non-Hispanic "other race" RNs. Non-Hispanic black LPNs have 42% higher odds of being active in nursing compared to non-Hispanic white LPNs.

Exhibit 32: Odds Ratios Predicting Probability RN/LPN Active

Parameter	RN Odds Ratio and 95% CI	LPN Odds Ratio and 95% CI

Unemployment rate (state, year) [a]	1.03*	1.01	1.05	0.99	0.96	1.03
Predicted hourly wage	0.97*	0.96	0.99	1.01	0.99	1.04
Age 30-34	0.69*	0.63	0.77	1.00	0.87	1.16
Age 35-39	0.89	0.79	1.00	1.08	0.92	1.26
Age 40 to 44	0.97	0.86	1.08	1.10	0.94	1.29
Age 45 to 49	1.12	0.99	1.27	1.08	0.92	1.27
Male [b]	0.71*	0.58	0.87	1.39*	1.03	1.88
Interaction between age and sex						
Age 30-34 * male	2.20*	1.59	3.06	1.36	0.77	2.41
Age 35-39 * male	2.81*	1.96	4.02	1.06	0.62	1.81
Age 40 to 44 * male	2.63*	1.87	3.70	1.31	0.76	2.27
Age 45 to 49 * male	1.94*	1.38	2.74	0.79	0.48	1.29
Year 2011 [b]	0.93	0.84	1.03	0.89	0.76	1.04
Year 2012 [b]	0.92	0.83	1.02	0.87	0.74	1.02
Year 2013 [b]	0.93	0.84	1.05	0.91	0.76	1.08
Year 2014 [b]	0.97	0.85	1.10	0.80*	0.66	0.98
Non-Hispanic black [b]	1.32*	1.17	1.49	1.42*	1.24	1.62
Non-Hispanic other race [b]	1.23*	1.10	1.37	0.91	0.77	1.09
Hispanic [b]	1.38*	1.19	1.60	1.04	0.88	1.22
Have nursing baccalaureate degree [b]	0.98	0.91	1.05	NA		
Having nursing graduate degree [b]	0.91	0.80	1.03	NA		
State's percentage of population residing in a suburban area	2.27*	1.33	3.89	1.26	0.54	2.95
State's percentage of population residing in a rural area	0.77	0.52	1.15	0.47*	0.26	0.84
Sample size	89,370			23,348		

Notes: Odds ratios and 95% confidence interval (CI) from logistic regression. * Statistically different from 1.0 at the 95% level. [a] State mean by year from the Bureau of Labor Statistics. [b] Comparison groups are female, year=2010, non-Hispanic white, age <30. Labor force participation regression uses only clinicians under age 50. Source: Analysis of the 2010-2014 files of the American Community Survey.

Cross-state Migration Patterns

Previous nursing projections for HRSA modeled two migration scenarios: (1) newly trained nurses remain in the state in which they are trained; and (2) nurses completing training migrate across states based on the relative distribution of growth in employment opportunities. Under this second scenario, states with faster employment growth might experience a net inflow of nurses trained in other states with fewer employment opportunities.

For this update, we start with the assumption that nurses will initially enter the workforce in the state where they took the NCLEX exam. We then model cross-state migration based on prediction equations estimated using logistic regression on with the 5-year (2010-2014) ACS file. Cross-state migration was modeled in two steps: 1) modeling whether a person moves out of a state, and 2) modeling whether a person moves into a state. Of 134,593 RNs in the 5-year file (with different nurses surveyed each year), 2,526 (1.9%) indicated working in a different state compared to a year ago. Of the 34,555 LPNs in this file there were 495 (1.4%) who indicated working in a different state compared to a year ago.

Analysis of nurse cross-state migration patterns suggests that: 1) The probability of migration declines with age, with nurses age 30 and below having the highest probability of migrating to another state; 2) Male RNs are more likely to move than female RNs; 3) RNs whose predicted hourly wages (a continuous variable) exceeds the national average wage are less likely to migrate to another state; 4) RNs with higher levels of educational attainment (bachelors and graduate-level degrees) are more likely to move across state; and 5) White RNs are more likely to relocate compared to other race/ethnicity groups (Exhibit 33).

Exhibit 33: Logistic Regression for Probability of Nurses Moving Out of State

	Registered Nurses			Licensed Practical Nurses		
Parameter	Odds Ratio	95% Confidence Interval		Odds Ratio	95% Confidence Interval	
Unemployment rate	0.97*	0.94	0.99	0.96	0.90	1.03
Predicted hourly wage	0.97*	0.96	0.99	1.04	0.99	1.10
Age group [a]						
30-34	0.53*	0.47	0.60	0.56*	0.42	0.75
35-39	0.40*	0.35	0.47	0.44*	0.32	0.61
40-44	0.35*	0.30	0.40	0.40*	0.29	0.55
45-49	0.29*	0.25	0.34	0.31*	0.22	0.44
50-54	0.24*	0.20	0.29	0.29*	0.20	0.40
55-59	0.23*	0.19	0.27	0.20*	0.14	0.30
Male [b]	1.52*	1.35	1.72	1.44*	1.10	1.89
Year [c]						
2011	0.96	0.84	1.09	1.19	0.88	1.61
2012	0.90	0.79	1.03	0.96	0.69	1.33
2013	0.93	0.81	1.07	1.20	0.86	1.68
2014	0.94	0.80	1.10	1.22	0.84	1.77
Education level [d]						
Bachelors	1.60*	1.45	1.76	NA		
Graduates	2.24*	1.93	2.61	NA		
Race/ethnicity [e]						
Hispanic	0.80*	0.68	0.94	1.13	0.90	1.42
Non-Hispanic black	0.73*	0.63	0.85	0.87	0.60	1.27
Non-Hispanic other	0.86	0.71	1.03	0.68	0.46	1.00
State's percentage of population residing in a rural area	1.04*	1.02	1.06	1.06*	1.02	1.17
Unweighted sample	N=134,593			N=34,555		

Note: Comparison groups are: [a] under age 30, [b] female, [c] 2010, [d] associates degree for RNs (not applicable for LPNs), and [e] non-Hispanic white. Source: Analysis of the 2010-2014 files of the American Community Survey. * Statistically different from 1.0 at the 5 percent level.

Using the ACS sample weights this analysis from 2010-2014 suggests that annually approximately 59,802 RNs and 12,220 LPNs change states. When modeling cross-state migration patterns, HWSM uses the above equations to generate a probability that each nurse will migrate out of the state. This probability is then compared to a random number between 0 and 1 using a uniform distribution. If the random number is below the estimated probability of moving then the nurse is moved out of that state.

To ensure that the national number and characteristics of nursing moving out of states matches the number and characteristics of nurses moving into states, when a nurse is simulated to move out of state that nurse is reassigned to another state using the distributions in Exhibit 34. Between 2010 and 2014, of the estimated 59,802 RNs who move to another state each year approximately 1% moved to Alabama and 8.1% moved to California.

Over time, projections of number of nurses exiting a state changes based on the characteristics of nurses in that state and overall number of nurses. The variation across states and across years reflects both the modeling of migration determinants and use of a random number generator to allocate moving nurses across the various states based on the geographic distributions described previously. As illustrated in Exhibit 35, Alaska is projected to have a net import of 179 RNs per year and 51 LPNs per year (i.e., more nurses will move into the state each year than move out of the state).

Exhibit 34: State Distribution of Annual Nurse In-migration

	Registered Nurses		Licensed Practical Nurses	
	Annual Number	National Distribution	Annual Number	National Distribution
AK	444	0.7%	79	0.6%
AL	595	1.0%	202	1.7%
AR	571	1.0%	194	1.6%
AZ	2,280	3.8%	302	2.5%
CA	4,864	8.1%	397	3.2%
CO	2,123	3.6%	312	2.6%
CT	624	1.0%	114	0.9%
DC	289	0.5%	30	0.2%
DE	224	0.4%	84	0.7%
FL	4,472	7.5%	956	7.8%
GA	2,287	3.8%	534	4.4%
HI	626	1.1%	218	1.8%
IA	604	1.0%	70	0.6%
ID	407	0.7%	120	1.0%
IL	1,253	2.1%	514	4.2%
IN	734	1.2%	285	2.3%
KS	838	1.4%	138	1.1%
KY	852	1.4%	118	1.0%
LA	577	1.0%	191	1.6%
MA	1,191	2.0%	118	1.0%
MD	1,672	2.8%	199	1.6%
ME	520	0.9%	105	0.9%
MI	819	1.4%	203	1.7%
MN	920	1.5%	159	1.3%
MO	1,492	2.5%	214	1.8%
MS	556	0.9%	162	1.3%
MT	384	0.6%	77	0.6%
NC	2,872	4.8%	355	2.9%
ND	266	0.4%	169	1.4%
NE	432	0.7%	19	0.2%
NH	433	0.7%	90	0.7%
NJ	1,089	1.8%	219	1.8%
NM	872	1.5%	184	1.5%
NV	817	1.4%	126	1.0%
NY	1,608	2.7%	477	3.9%
OH	1,652	2.8%	347	2.8%
OK	521	0.9%	153	1.3%
OR	1,020	1.7%	30	0.2%
PA	1,921	3.2%	355	2.9%
RI	138	0.2%	67	0.6%
SC	1,157	1.9%	193	1.6%
SD	120	0.2%	41	0.3%
TN	1,503	2.5%	468	3.8%
TX	4,636	7.8%	1,584	13.0%
UT	477	0.8%	63	0.5%
VA	2,186	3.7%	504	4.1%
VT	256	0.4%	35	0.3%
WA	1,983	3.3%	217	1.8%
WI	934	1.6%	138	1.1%
WV	427	0.7%	262	2.1%
WY	264	0.4%	29	0.2%
U.S.	59,802	100%	12,220	100%

Source: Analysis of the 2010-2014 files of the American Community Survey.

Exhibit 35: RNs Average Annual Net Cross State Migration, 2015-2030

State	Average Annual Migration (Move-in Minus Move-Out)	Estimated 2015 FTE Supply	Projected 2030 FTE Supply
AK	179	16,400	18,400
AL	-920	68,000	85,100
AR	-242	28,400	42,100
AZ	1,185	65,700	99,900
CA	775	277,400	343,400
CO	1,291	41,900	72,500
CT	-14	34,000	43,500
DC	175	1,800	8,800
DE	80	9,600	14,000
FL	1,004	170,600	293,700
GA	893	77,200	98,800
HI	332	10,900	19,800
IA	-418	32,500	45,400
ID	139	11,200	18,900
IL	-1,135	116,300	143,000
IN	-834	62,900	89,300
KS	-61	29,500	47,500
KY	-510	44,900	64,200
LA	-330	40,600	52,000
MA	-364	73,200	91,300
MD	643	58,700	86,000
ME	205	14,600	21,200
MI	-1,076	91,600	110,500
MN	-353	56,200	71,800
MO	-120	59,600	89,900
MS	-349	29,100	42,500
MT	-18	9,600	12,300
NC	1,447	90,000	135,100
ND	-162	7,600	9,900
NE	-317	20,300	24,700
NH	111	15,500	21,300
NJ	-104	81,700	90,800
NM	520	15,900	31,300
NV	613	18,300	33,900
NY	-2,226	174,100	213,400
OH	-1,270	122,800	181,900
OK	-414	32,500	46,100
OR	523	30,400	41,100
PA	-783	133,200	168,500
RI	-120	11,000	15,000
SC	367	36,900	52,100
SD	-403	10,300	11,700
TN	144	61,000	90,600
TX	509	180,500	253,400
UT	-124	20,000	33,500
VA	718	67,900	109,200
VT	115	6,000	9,300
WA	1,049	56,700	85,300
WI	-318	58,100	78,200
WV	-99	18,800	25,200
WY	67	4,200	8,300

Exhibit 36: LPNs Average Annual Net Cross State Migration, 2015-2030

State	Average Annual Migration (Move-in Minus Move-Out)	Estimated 2015 FTE Supply	Projected 2030 FTE Supply
AK	51	1,700	2,000
AL	-49	22,200	20,500
AR	-69	12,200	17,800
AZ	165	9,100	12,200
CA	-542	72,000	121,000
CO	201	6,900	10,400
CT	8	9,600	11,000
DC	16	900	1,800
DE	24	2,900	4,200
FL	225	54,200	73,600
GA	193	26,300	25,800
HI	171	2,300	4,700
IA	-163	7,900	13,000
ID	55	2,500	4,300
IL	116	26,500	34,400
IN	31	19,900	19,900
KS	-105	8,400	14,400
KY	-136	12,600	14,400
LA	-57	18,400	20,700
MA	-47	14,400	16,500
MD	32	13,300	11,300
ME	59	2,000	3,400
MI	-121	21,500	24,800
MN	-126	16,200	24,700
MO	-126	20,000	23,200
MS	-79	9,900	11,800
MT	12	2,300	2,800
NC	55	22,900	24,400
ND	81	2,500	3,900
NE	-90	6,200	6,000
NH	34	4,700	4,700
NJ	-55	19,400	30,500
NM	103	3,000	4,900
NV	87	3,200	4,200
NY	-57	52,400	58,900
OH	-270	42,500	54,900
OK	-149	14,800	18,400
OR	-39	3,100	4,900
PA	-212	49,300	48,600
RI	46	2,000	2,300
SC	72	8,000	8,200
SD	-15	2,100	2,800
TN	109	24,000	29,600
TX	385	70,900	80,900
UT	-16	2,900	6,700
VA	84	25,500	32,200
VT	-2	1,800	2,500
WA	56	11,200	13,600
WI	-48	12,600	16,300
WV	114	7,600	10,900
WY	-15	1,000	1,800

B. Modeling Demand

The projected demand for nurses was derived from the common model outlined in Chapter III. Predicted probabilities were applied to the simulated micro-data set for future years to obtain projected service use specific to the settings that employ nurses. For example, projected growth in hospital inpatient days and emergency visits was used to project growth in demand for RNs and LPNs employed in hospitals. For work settings outside the traditional health care system, HWSM used the size of the population most likely to use those services to project demand (Exhibit 37).

HWSM used provider staffing patterns to project demand for health care workers by delivery setting based on the demand for health care services. As illustrated in Exhibit 37, nurses were found in almost all care delivery settings. Nurse staffing patterns were calculated using the portion of national FTE nurses providing care in each setting, and dividing by current estimates of the workload driver in that work setting. The baseline demand projections assumed these ratios remained constant over time. The demand for nurses in academia was based on the estimated number of nursing graduates, assuming current ratios of nurse educators-to-students remained constant. Estimates of the distribution of nurses across employment settings came from analysis of the 2015 OES. We used data from the 2008 National Sample Survey of Registered Nurses to break our hospital totals from the OES data into inpatient and emergency departments, and to break out nurses in education to those providing school health and those in nursing education.[137]

National staffing ratios by care delivery setting at baseline were applied to the projected service use to obtain the staffing requirement by setting. These were aggregated to obtain the total demand for nurses. Projections were made at the state level and summed to produce national estimates.

Exhibit 37: Summary of Nursing Workload Drivers by Work Setting

	Distribution (%)		Full Time Equivalents		Workload[b]		Staffing Ratios *(workload per nurse)*	
	RNs[a]	LPNs[a]	RNs	LPNs	Volume	Metric	RNs	LPNs
Office	7.5	14.5	211,100	117,200	976,507,000	Visits	4,626	8,332
Outpatient	4.0	3.1	112,500	25,500	36,889,000	Visits	328	1,447
Inpatient	52.8	16.6	1,485,300	134,500	145,137,000	Days	98	1,079
Emergency	8.5	<0.1	236,600	--	119,144,000	Visits	504	--
Home Health Care[e]	6.3		178,500		228.5 million	Visits	1,280[c]	
		12.2		99,300	150.8 million	Visits		1,519[c]
Nursing Home[e]	5.6	31.3	156,700	252,200	19,769,000	Population 75+	126	78
Residential Care[e]	1.7	8.8	48,300	71,200	19,769,000	Population 75+	409	278
School Health	3.1	<0.1	85,700	--	49,788,000	Students	581	--
Nurse Education	3.6	0.3	101,000	2,100	158,000 (RNs) 51,000 (LPNs)	NCLEX 1st time US-educated takers	2.1 (RN+LPN)	24.3 (LPN)
All Other	6.8	13.0	190,400	117,700	318,857,000	Population	1,675	2,961
Total	**100**	**100**	**2,806,100 [d]**	**809,700[d]**				

Note: Numbers may not sum to 100 percent because of rounding. Sources: [a] BLS Occupational Employment Statistics 2015 (with RN distribution modified for nurse education, school health and emergency departments based on the 2008 National Sample Survey of Registered Nurses ; [b] Estimates from HWSM; [c] Estimates based on working 240 days/year and 4.96 home health visits/day for RNs and 5.9 visits/day for LPNs. http://www.nahc.org/assets/1/7/10hc_stats.pdf Published estimates for national home health visits are unavailable, so the total visit estimates presented here were calculated based on published nurse workload data plus estimates of total nurses providing home health services; [d] American Community Survey, 2014; [e] Staffing estimates for nurses in long term care settings were updated in 2017 (see and Exhibit 23).

C. Baseline and Alternative Nursing Workforce Projections

Supply Projections

HWSM can project future nurse supply under multiple scenarios to illustrate the sensitivity of the model to the continuation of trends in key supply determinants. The status quo scenario models the continuation of current numbers of nurses completing their nursing education and current patterns of labor force participation. As discussed previously, labor force participation (attrition, being temporarily out of the workforce, and hours worked patterns) varies by nurse demographics, education level, and other characteristics of the nurse or community. The status quo scenario models the continuation of these patterns taking into account the changing demographic and changing education levels of the nursing workforce.

Alternative supply scenarios modeled include the impacts of: 1) retiring two years earlier or delaying retirement by two years, on average; 2) graduating 10% more or 10% fewer nurses annually than the status quo; 3) and a gradual 5 % increase or 5% decrease in average nurse productivity levels. The early or delayed retirement scenarios simply shift workforce attrition patterns for nurses age 50 and older by ±2 years. For example, a nurse who would have retired at age 65 under the status quo scenario would now retire at age 63 under the Early Retirement scenario and would retire at age 67 under the Delayed Retirement scenario. The ±5% change in productivity scenarios assume that each year between 2014 and 2030 there is small (about 0.31%) change in nurse productivity such that cumulatively the impact reaches ±5% impact by year 2030 versus year 2014. Productivity is defined for purpose of supply modeling as the number of patients that can be treated by 1 FTE nurse over the course of a year (as defined by the staffing levels in Exhibit 37). Productivity changes could occur because of changes in technology or practice patterns, or through changes in average hours worked. A ±5% productivity change is equivalent to ±5% change in FTE supply.

Demand Projections

The Status quo scenario for modeling demand assumes that recent (2009-2014) patterns of care use and delivery will remain unchanged, but considers population growth and aging as well as expanded insurance coverage that has occurred and is projected to occur under the Affordable Care Act. Care use and delivery patterns likely will change over time; however, there is limited published information or data to use for modeling how care use patterns might change over time and the nursing workforce implications of changes in care use or delivery. Using information from several published demonstrations of emerging care delivery models, we simulated the potential impact of such changes on the nursing workforce.

The following examples combine information from the published literature with HWSM to illustrate the changing roles of RNs and LPNs within a care coordination model. These models are currently part of ongoing studies on nurse utilization in coordinated care settings. Each pilot study utilizes RNs in roles such as nurse care managers working with other staff to coordinate care, improve patient self-education and adherence to treatment plans.

The pilot studies also illustrate how RN care managers coordinate with pharmacists, behavioral health providers, and licensed clinical social workers. Under the shifting roles of RNs in these and other emerging care models focused on improving population health, service demand is reduced and redirected from higher cost hospital inpatient and emergency department settings to more clinically appropriate outpatient and community-based care settings. As a result, some future reductions in clinical RN staffing in hospital settings are possible.

The Camden Coalition (Camden, New Jersey) provides health services to a patient population that experiences multiple social barriers to accessing health services.[139] RNs are utilized in care manager roles to provide critical support and oversight for patients' transition into primary care. Camden Coalition's RN model focuses on patient engagement; patient care is tailored to the specific needs of each patient to ensure a more effective transition into primary care. To date, hospital admissions by "super users," or patients who frequently utilize hospital services, declined by 57%, while emergency department visits declined by 33% and the cost of care decreased by 56%.[140] The nursing workforce implications of implementing such a model at the national level could be reductions in demand of about 158,000 RNs and 14,000 LPNs in hospital settings in 2030, assuming super users account for 4% of all visits to the emergency room[141] and 14% of inpatient hospital days.[142]

CareOregon (Portland, Oregon) is a non-profit Medicaid managed care plan which serves 128,000 low-income residents representative of one-third of the state's Medicaid enrollees.[143] Two-thirds of patients have one of 12 common chronic conditions including but not limited to diabetes, depression, and chronic heart failure. Two-thirds of the health plan members are children and more than 5,700 adults are dual-eligible for Medicaid and Medicare services. CareOregon provides two health care tracks: (1) *Primary Care Renewal* (a patient-centered medical home initiative) works through safety net clinics; and (2) *Care Support*, a multidisciplinary management program for members with high risk of poor health outcomes. Both health care tracks utilize nurse care managers on care coordination teams working with social workers and care coordination assistants to monitor patients and identify risks before health crises occur. Nurse care managers' functions include coordination of services, patient education, and treatment adherence. Care Support reported decreases in non-obstetric hospital admissions and emergency department visits of about 34%. Offering such a model to all Medicaid beneficiaries nationally could result in lower hospital-based RN and LPN FTE demand in 2030 by about 151,000 and 11,000, respectively, resulting from lowered levels of service use in the inpatient and emergency settings.

Community Care of North Carolina (CCNC) (Raleigh, North Carolina) utilizes nurses as managers in the provision of services for chronically ill patients.[144] The patient population includes the Aged, Blind, and Disabled sub-population which accounts for nearly 70% of the service dollars but fewer than 30% of program recipients. Nurse care managers work with physicians and pharmacists to provide coordinated patient care. Duties include but are not limited to: medication reconciliation, coordination with medical homes and primary care providers providing patient care and with community agencies and other local resources providing support services for the Medicaid population. CCNC reported the following results between 2006 and 2011: (1) admission rates decreased by 21%; and (2) emergency department visits decreased by 32.8%. Implementing this program for a similar national Medicaid population could reduction the projected 2030 FTE demand for hospital-based RNs and LPNs by about 103,000 and 7,000, respectively.

These illustrative examples of pilot studies using nurses to better manage patient care illustrate that while demand for nurses might rise for some roles (e.g., care management), the overall demand for nursing services could fall in hospital settings. In general, the literature suggests that the decline in nurses resulting from lower health care utilization will more than exceed the increase in demand for nurses for care management. Hence, the demand projections presented in this report might be high and thus understate projected surpluses if current supply trends continue.

Population Health

While the above pilot studies focus on the short-term implications on care utilization and staffing among select high-utilization subsets of the population, there are broader trends in population health that have long term implications for the nurse workforce. New policy guidelines, provisions in the ACA, and new reimbursement models are designed to promote preventive care with the potential to improve the health of the entire population (beyond just high risk, high utilization subpopulations). Examples include guidelines and reimbursement for counseling and treatment to promote a healthful diet and physical activity to individuals at high risk for developing cardiovascular disease or diabetes, for smoking cessation, and to improve control of blood pressure, cholesterol levels, and hemoglobin A1c levels.[16–18]

Building on a recently published study[145] and using a Markov-based microsimulation approach described in detail elsewhere[22–24] we modeled the potential long term health impacts and nurse demand of achieving the following population health goals:

- **Sustained 5% body weight loss for overweight and obese adults**: Counseling and pharmacotherapy have been shown to reduce excess body weight by 5% or more—thus lowing risk for diabetes, cardiovascular disease, and other morbidity.[24]
- **Improved blood pressure, cholesterol, and blood glucose levels**: Published trials report that among patients with elevated levels, counseling and pharmacotherapy can improve cholesterol, blood pressure, and hemoglobin A1c levels.[30–32]

- **Smoking cessation**: Smoking cessation can reduce risk for cancer, heart disease and other morbidity.[33]

The model's prediction equations came from published clinical trials and observational studies, and the simulation was conducted using a nationally representative sample of adults constructed using the 2013-2014 National Health and Nutrition Examination Survey combined with national population projections. Outcomes from this model were then used in HWSM to model the demand for health care services and nurses.

As reported elsewhere cumulative between 2015 and 2030 achieving these population health goals could reduce cases of heart disease by 10.2 million, stroke incidence by 3.2 million, myocardial infarction incidence by 3 million, and incidence of cancer and other diseases.[34] This reduction in incidence/prevalence would reduce demand for nurses. However, the improved health of the population would also reduce mortality, and if the modeled goals were achieved the projected size of the population in 2030 would be 6.3 million higher than current Census Bureau projections. These additional 6.3 million people would be primarily elderly—including about 2.9 million age 75 or older, 2.3 million age 65 to 74, 1 million age 45 to 64, and approximately 30,000 adults under age 45.

Compared to the baseline demand scenario, by 2030 national demand for RNs and LPNs under this population health scenario would be *higher* by approximately 105,800 FTEs and 69,500 FTEs, respectively, to support the larger population even though per capita use of nursing services would be lower. This scenario suggests that efforts to improve population health might reduce demand for nurses in the short term, but to the extent that preventive care increases longevity overall demand for nurses could rise in the long term.

Modeling Supply and Demand by Metropolitan versus Non-metropolitan Location

State-level indicators of metropolitan/non-metropolitan for modeling nurse supply in 2014 came from analysis of the ACS. Using USDA 2013 Rural-Urban Continuum Codes (RUCC) we classified each county or county subpart in a PUMA as metropolitan or non-metropolitan.[1] Metro and non-metro county classifications are based on Office of Management and Budget (OMB) delineation as of February 2013. OMB defines metro counties with RUCC values of 1,2, or 3 and all other counties are defined as non-metro. The Rural-Urban Continuum Codes (RUCC) file was merged with the PUMA-county crosswalk file available through the Missouri Data Center which allows us to map PUMA to a county. Thus we were able to assign a PUMA as either metro or non-metro based on the RUCC definitions. Finally, the PUMA-county crosswalk file including the metro/non-metro indicator was merged with the ACS file in order to generate statistics by metro and non-metro.

Indicators of metropolitan/non-metropolitan to model demand for nurses is based each person’s metropolitan status as indicated in the BRFSS. Metropolitan status was based on the “MSCODE” variable in the 2013-2014 BRFSS survey data. Based on the BRFSS variable metropolitan area is defined where one of the following criteria is fulfilled: 1) In the center city of an MSA; 2) Outside the center city of an MSA but inside the county containing the center city; 3) Inside a suburban county of the MSA; or 4) In an MSA that has no center city.

Given the demographics and health care use patterns of the population in metropolitan versus non-metropolitan areas, the population living in metropolitan areas would utilize approximately 83% of the nation’s RN services. An estimated 85% of FTE RN supply is in metropolitan areas. Though the 83% and 85% are similar, many patients in non-metropolitan areas might travel to metropolitan areas to receive specialized care, and nurse staffing patterns could differ between metropolitan and non-metropolitan areas both to reflect differences in patient acuity levels and differences in productivity due to patient volume.

X. The Physician, Advanced Practice Nurse and Physician Assistant Model Components (updated 2014)

This chapter summarizes the methodology for projecting the national supply and demand for select physician specialties, advanced practice nurses (APNs) and physician assistants (PAs). Projections also were made at the U.S. census division and region levels for detailed specialties, and at the state level for specialty categories. Supply and demand projections were made for 36 physician specialties, three APN professions (nurse practitioners [NPs], certified nurse midwives [CNMs], and certified registered nurse anesthetists [CRNAs]) and PAs.

A. Primary Care Provider Model

This section summarizes the methodology for projecting the supply and demand for primary care physicians, advanced practice nurses (APNs) and physician assistants (PAs) at the national, U.S. census division and region levels by specialty. Selected specialties identifying primary care providers include general and family medicine, general internal medicine, geriatrics, and general pediatrics.

Estimating the Current Active Workforce Supply

The source for estimating the current active supply of physicians at the U.S. region and state level is the 2013 American Medical Association (AMA) Master File Extract. The analysis was limited to active physicians. Because the AMA file is known to misclassify older physicians who have retired as ‘active’, those over age 75 were deleted form the analysis file. In addition, retired physicians between 50 to 75 years of age were identified and deleted based on predicted probabilities derived from a logistic regression on age and specialty. In addition to adjusting for misclassification of retirees as active physicians, the AMA Masterfile was adjusted for undercounting hospitalists, a large proportion of who are listed under the specialty in which they received their training.

The method to separate hospitalists trained in primary care from physicians actually providing office-based primary care services builds on ongoing work by AAMC’s Center for Workforce Studies. Using the NPI numbers from 2014 Medicare fee-for-service billing records and the AMA Masterfile, physicians where close to 100% of their Evaluation and Management billing was hospital-based were identified as hospitalists in the AMA Masterfile. About twenty five thousand hospitalist physicians were listed in the AMA Masterfile as general internists, family physicians, or geriatricians. Hospitalists trained in pediatrics could not be identified using Medicare billing records. A comparison of the counts from the original AMA file with the new file with hospitalists removed provided the discount factor. The base numbers in 2013 AMA Masterfile were then discounted by that factor.

The base year counts for APNs come from the 2013 National Plan and Provider Enumeration System (NPPES) which contains a unique identifier (National Provider Identification, NPI) for each clinician. The 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey was utilized to develop the base year counts for PAs by age and sex.

Modeling New Entrants

The mechanism for adding new entrants to the workforce each year is the creation of a “synthetic” population of the profession based on the number and characteristics of recent graduates in each occupation. As described in section II.B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years.

Estimates of total annual new physicians, APNs, and PAs and the specialty distribution came from multiple sources. The primary sources of data on characteristics of new graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators, the 2013 AMA Master File and the American Board of Medical Specialties (ABMS) for physician specialties. Numbers and characteristics of new NPs, in the workforce entrants come from the 2012 American Association of Colleges of Nursing (AACN) survey. The 2013 NCCPA Professional Profile is the primary source for characteristics on new PA workforce entrants and the Physician Assistants Education Association the source of data on new PAs trained. Exhibit 15 summarizes the age and sex distribution of new entrants to the primary care workforce.

After simulating the age and sex of the new entrants, the state where new providers would practice was simulated based on a model that regressed the probability of practicing in a state on the relative difference between the projected supply and demand for services for that kind of provider in that state.

Exhibit 38: Age and Sex Distribution of New Physicians, APNs and PAs in Primary Care

Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution <25	26-30	31-40	>41
Primary Care Physicians						
General & Family Medicine	3,270	55%	0%	30%	60%	9%
General Internal Medicine	3,301	44%	0%	34%	60%	7%
Geriatrics	279	58%	0%	15%	77%	8%
General Pediatrics	1,642	71%	0%	49%	48%	3%
Total	29,032	45%	0%	18%	75%	7%
Advanced Practice Nurses & Physician Assts.						
Nurse Practitioner	6080[a]	95%	2%	22%	32%	44%
Physician Assistant	2,182 -2,570[b]	64%	9%	38%	42%	11%

Sources: 2013 AMA Master File, 2012-2013 AAMC GME Census, 2012 American Association of Colleges of Nursing (AACN) survey, 2013 NCCPA Professional Profile, Physician Assistance Education Association. [a] Estimates of new NPs trained reflect analysis of the 2012 NSSNP of the proportion of new NPs in primary care that work in a position requiring NP licensure. [b] Grows from 2,128 to 2,570 between 2013 and 2025 reflecting projected growth in number and average size of PA programs. Primary sources of data on new graduates include the AMA Masterfile for physicians, PAEA and the NCCPA for Physician Assistants, and the AACN for APNs.

Modeling Workforce Attrition

Data sources for modeling attrition patterns of physicians by individual specialty are limited. The primary source of attrition information for physicians in HWSM is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire in the upcoming five years. The retirement patterns from this source were compared to the AAMC's 2006 Survey of Physicians over Age 50 which collected information on age at retirement or age expecting to retire and found to be comparable. However, the Florida survey was used because it has a larger sample size and more detailed information on individual specialties.

Attrition rates also differ by medical specialty. This analysis used the age, sex and specialty specific attrition rates from the 2012 and 2013 Florida Bi-annual Physician Licensure Survey to calculate the attrition rates for physician providers with primary care specialties. Attrition patterns for APNs and PAs were unavailable. As a result, attrition patterns for primary care physicians were used as proxies. Attrition patterns were combined with age-sex specific mortality rates from the Centers for Disease Control and Prevention (CDC) adjusted downward to account for lower mortality of technical and professional occupations.[10,146]

Modeling Hours Worked

Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 bi-annual Physician Licensure Workforce Survey (n=18,016) of physicians in Florida who renewed their license.[a] Hours worked patterns differed by specialty in addition to age and sex. Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable. Explanatory variables included indicators variables for specialty, age group, female sex, and age-group by sex interaction. Average hours worked by primary care physicians varied by specialty. FTE for primary care physicians for each specialty was defined as the average hours worked per week in that specialty. These were 40.4 hours for physicians in family practice, 44 hours for general internists, 40.5 for pediatricians and geriatricians. Exhibit 16 shows hours worked pattern by physician age and sex. Young, male physicians tended to work more hours per week than their female counterparts, while the sex gap in hours worked largely disappeared after age 55.

Similar regression analyses were conducted using 2013 NCCPA licensure files to model hours worked patterns of PAs, and the 2012 National Sample Survey of Nurse Practitioners (*NSSNP*) to model hours worked patterns for NPs. However, no sex-by-age interaction terms were included for APNs because the large majority is female. An FTE was calculated for these occupations as the average hours worked among clinicians working at least 20 hours per week.

On average, NPs in primary care worked 32 hours weekly in patient care related activities. Average weekly hours worked patterns varied slightly across PA primary care specialties, ranging from 39 hours (pediatrics) to 42 hours (general internal medicine and geriatrics). PAs in general family practice worked on average about 41 hours weekly.

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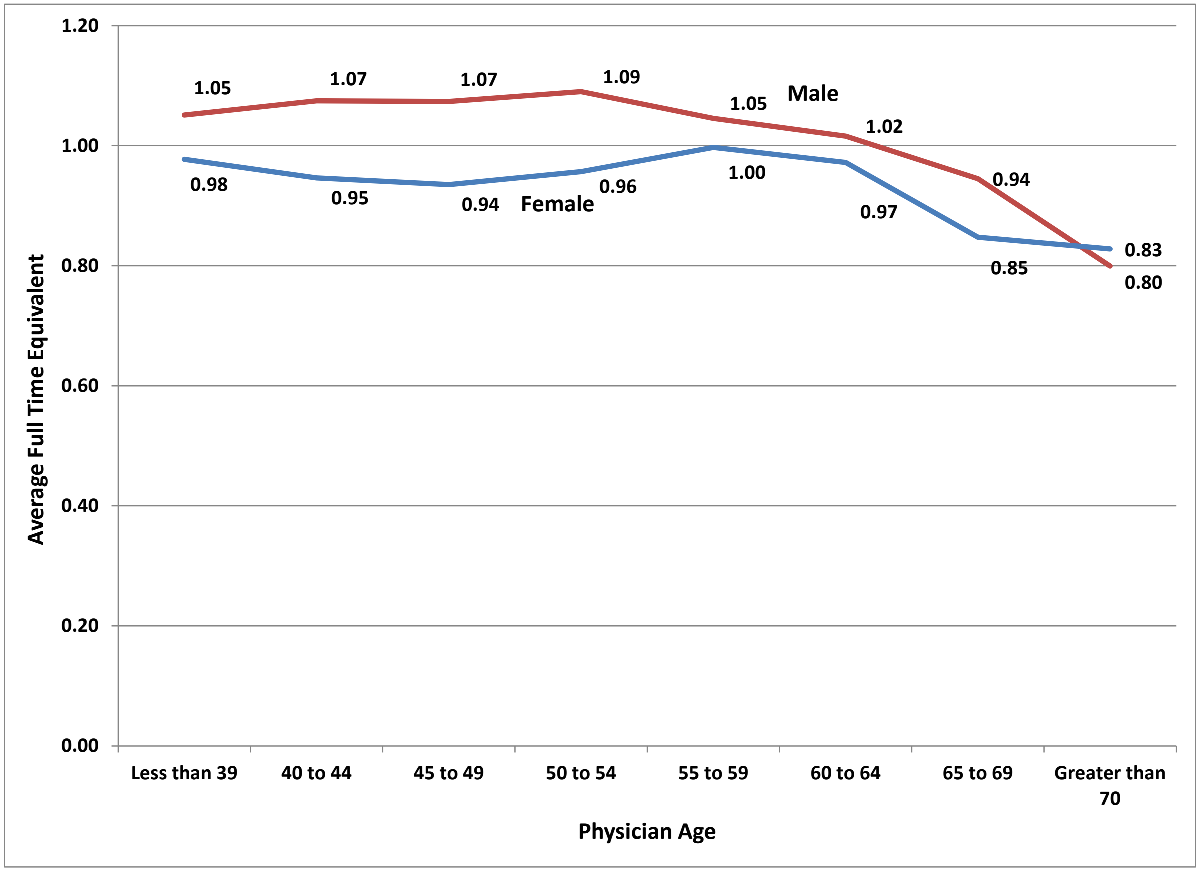
[a] Analysis of Maryland's physician licensure files found similar work patterns by physician age, sex, and specialty

Exhibit 39: Primary Care Physician Hours Worked Patterns, in FTEs



Sources: Florida 2012-2013 bi-annual Physician Licensure Workforce Survey

Developing Primary Care Physician, APN and PA Demand Projections

Consistent with the approach adopted for other health professions modeled, the projected demand for physicians, APNs and PAs was derived from the common model outlined in Chapter III. Predicted probabilities were applied on the simulated micro-data set for future years through 2025 to obtain projected service use specific to the settings where these providers work. For work settings outside the traditional health care system (e.g., school health) HWSM used the size of the population most likely to use those services. Due to small sample sizes HWSM does not model occupation-setting combinations where service volume is small (e.g., physicians providing care in home health and residential facilities). Also, the proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time.

Demand for primary care physician, was tied to projected demand for office visits. In addition, the demand was tied to a specific proportion of inpatient services to account for hospital rounds conducted by primary care physicians.

Prediction equations for use of office and outpatient services were estimated using Poisson regression with 2008-2012 MEPS data. Separate regressions were estimated for children and adults, and by physician specialty. The dependent variables were annual office visits and annual outpatient visits for each specialty. Explanatory variables consisted of the patient characteristics, socioeconomic and insurance variables, and health status variables described previously.

To account for the demand for primary care clinicians for hospital rounds, HWSM developed predictive equations for inpatient days by relevant population groups. For example, the demand for Geriatricians was derived from the expected number of hospital days in the age 75plus age group, while the demand for Pediatricians in a hospital was derived from the expected number among the 18 and younger age group (Exhibit 40).

Exhibit 40: Hospital Inpatient Demand Drivers by Primary Care Physicians

Medical Specialty	Workload Driver
Family Practice	Inpatient days for all hospitalizations
General Pediatrics	Inpatient days for all hospitalizations by patients age <18
Internal Medicine	Inpatient days for all hospitalizations by patients age 18+
Gerontology	Inpatient days for all hospitalizations by patients age 75+

Source: HWSM estimates from the Medical Expenditure Panel Survey (2008-2012) and the 2012 Nationwide Inpatient Sample

Predicted number of inpatient days were developed using the common methodology described in Section III.B of this report, and aggregated across the relevant population groups. Current national estimates of the workload driver for primary care services and physician distribution are shown in Exhibit 41.

Exhibit 41: Summary of National Physician Workload Measures for Primary Care, 2013

	Office Visits	Outpatient Visits	Inpatient Days
Primary Care Services			
Family Practice	214,093,000	5,542,000	183,050,000 [a]
General IM	139,668,000	887,000	135,154,000 [b]
Pediatrics	130,940,000	614,000	47,896,000 [c]
Geriatrics	1,069,000	28,000	37,523,000 [d]
Primary Care Physicians			
Family Practice	90,260	2,250	2,280
General IM	73,290	420	19,830
Pediatrics	44,310	210	4,380
Geriatrics	2,640	70	870
Physician Staffing Ratio			
Family Practice	2,372	2,463	80,285
General IM	1,906	2,112	6,816
Pediatrics	2,955	2,924	10,935
Geriatrics	405	400	43,130

Sources: HWSM Projections for 2013 and analysis of 2013 AMA Master File. Distributions by care delivery site based on multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey, 2010 American Board of Internal Medicine survey, specialty-specific surveys.

Notes: [a] All hospitalizations. [b] All hospitalizations by patients age <18, [c] All hospitalizations by patients age 18+, [d] All hospitalizations by patients age 75+.

HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting (Exhibit 41). These ratios were then applied to projections of future demand for services that assumes the status quo in terms of care use and delivery patterns. Estimated FTE requirements to care for each person were then aggregated and inflated by the number of Physicians required to overcome primary care provider shortages in Health Professions Shortage Areas (HPSA)[147] to obtain the total demand for primary care physicians.

Because of limitations in identifying which visits/hospitalizations resulted in consultation with a NP and because NPPES, the data source used to determine the baseline NP supply did not identify the practice site, the demand for NPs in primary care were assumed to grow in the same rate as the demand for primary care physicians. This implies that the physician to NP staffing ratio remains the same for the duration of the projection period.

However, for PAs, a process similar to estimating the physician staffing ratio was used to estimate current and project future FTE demand for PAs. Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each primary care delivery setting and specialty, and the national volume of care in each care setting and specialty, divided by the number of FTE PAs in that setting, provided estimates of PA FTE required per unit of health care service delivered in that setting (Exhibit 42).

Exhibit 42: Summary of FTE Physician Assistant Distribution by Care Delivery Site for Primary Care, 2013

Specialty	Office	Outpatient	Inpatient
Primary Care Services			
Family Practice	214,093,000	5,542,000	183,050,000 [a]
General IM	139,668,000	887,000	135,154,000 [b]
Pediatrics	130,940,000	614,000	47,896,000 [c]
Geriatrics	1,069,000	28,000	37,523,000 [d]
Primary Care Physician Assistant			
Family Practice	11,000	10,230	210
General Internal Medicine	3,870	2,490	920
General Pediatrics	1,800	840	530
Geriatrics	60	80	30
Primary Care Physician Assistant Staffing Ratio			
Family Practice	19,463	542	871,667
General Internal Medicine	36,090	356	146,907
General Pediatrics	72,744	731	90,370
Geriatrics	17,817	350	1,250,767

Source: HWSM Projections for 2013 and Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey.
Notes: [a] All hospitalizations. [b] All hospitalizations by patients age <18, [c] All hospitalizations by patients age 18+, [d] All hospitalizations by patients age 75+.

B. Internal Medicine Subspecialty Model

This section describes the supply and demand models of physicians and PAs in 11 internal medicine subspecialties (Exhibit 43) and the supply and demand for physicians and nurse practitioners in critical care medicine. Estimating the Current Active Workforce Supply

The source for estimating the current active supply of physicians at the U.S. state and region level is the 2013 American Medical Association (AMA) Master File Extract adjusted for misclassification of older (aged 75 or over) retired physicians as "active". The base year counts and age sex characteristics for PAs come from the 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey. The counts for NPs in critical care come from NPPES, while the age sex distribution of from the ACS is used to assign the age-sex characteristics.

Exhibit 43: Summary of Internal Medicine Specialties

Specialty	Description
Allergy and Immunology	The prevention, diagnosis and treatment of problems with the immune system.
Cardiology	The diagnosis, intervention, treatment, and care of the heart and its related diseases.
Critical Care[a]	The treatment and care of a critically ill or critically injured patient. Critical illness acutely impairs one or more vital organ systems such that there is a high probability of imminent or life-threatening deterioration in the patient's condition.
Dermatology	The diagnosis, treatment, and prevention of diseases of the skin, hair, nails, oral cavity and genitals.
Endocrinology	The diagnosis and treatment of diseases related to hormones and human functions as the coordination of metabolism, respiration, reproduction, sensory perception, and movement.
Gastroenterology	The study diagnosis, and treatment of disorders of the digestive system.
Hematology/Oncology	The diagnosis and treatment of blood disorders and cancer.
Infectious Diseases	The diagnosis and treatment of infectious diseases
Neonatal/Perinatal Medicine	A subspecialty of pediatrics, concerns the care of critically ill newborn and premature infants
Nephrology	The diagnosis and treatment of kidney diseases
Pulmonology	The diagnosis and treatment of disease, conditions, and abnormalities of the lungs and cardio-pulmonary system.
Rheumatology	The diagnosis and treatment of arthritis and other rheumatic diseases that affect the joints, muscles, bones and sometimes other internal organs.

Note [a] A small number of physicians categorized as critical care include designations such as critical care surgery, critical care anesthesiology, and neonatal critical care.

Modeling New Entrants

The mechanism for adding new entrants to this workforce is done via the creation of a "synthetic" population based on the number and characteristics of recent graduates in each internal medicine specialty. As described in Section II.B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years. The primary sources of data on new graduates are the AMA Masterfile for physicians, the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrations, and the American Board of Medical Specialties (ABMS) for physician specialties (Exhibit 44). Numbers and characteristics of new PA come from the Physician Assistant Education Association (PAEA) survey and the NCCPA for physician assistants. The number of new NPs in critical care comes from the 2012 American Association of Colleges of Nursing (AACN) survey.

After simulating the age and sex of the new entrants, the region where new providers would practice was simulated based on a model that regressed the probability of practicing in a region on the relative difference between the projected supply and demand for services in that region.

Exhibit 44: Age and Sex Distribution of New Physicians, Physician Assistants and Nurse Practitioners by Internal Medicine Specialty

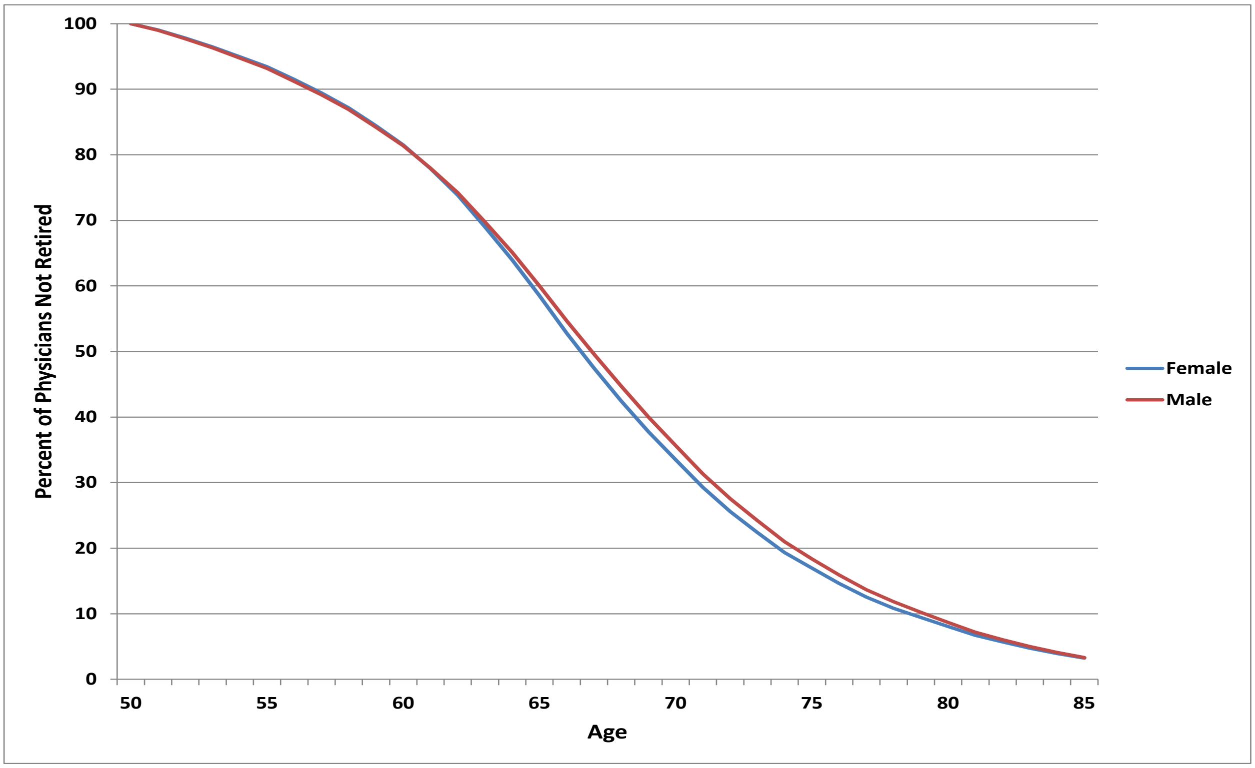
Internal Medicine Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution			
			<25	26-30	31-40	>41
Physician						
Allergy & Immunology	128	63%	0%	6%	90%	4%
Cardiology	937	24%	0%	1%	91%	6%
Critical Care	249	31%	0%	1%	90%	9%
Dermatology	498	64%	0%	19%	78%	3%
Endocrinology	347	67%	0%	5%	90%	5%
Gastroenterology	530	30%	0%	1%	94%	5%
Hematology/Oncology	662	43%	0%	1%	90%	9%
Infectious Diseases	393	58%	0%	3%	92%	6%
Neonatal/Perinatal Medicine	203	63%	0%	1%	90%	9%
Nephrology	483	38%	0%	3%	88%	8%
Pulmonology	535	29%	0%	1%	91%	8%
Rheumatology	246	67%	0%	3%	89%	8%
Non-Physician Clinician						
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%
Nurse Practitioner	12,789[b]	95%	19%	47%	29%	5%

Source: 2013 AMA Master File and 2012-2013 AAMC GME Census. 2012 American Association of Colleges of Nursing (AACN) survey, 2013 NCCPA Professional Profile, Physician Assistance Education Association. [a] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs. [b] Estimates of new NPs trained reflect analysis of the 2012 NSSRN of the proportion of new NPs that work in a position requiring NP licensure.

Modeling Workforce Attrition

As in the case of primary care, the main source of retirement information is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey. Retirement rates differ by medical specialty; specialties such as allergy & immunology, cardiology, and gastroenterology tend to have later retirements compared to other specialties. Age-sex specific rates calculated form the Florida Bi-annual Physician Licensure Survey, were combining with the age-sex specific mortality rates to derive the overall attrition rate. Exhibit 45 shows that male and female physicians have similar attrition patterns after adjusting for the slightly higher mortality rates among men. Attrition patterns for APNs and PAs were unavailable. As a result, attrition patterns of family physicians were used as proxies.

Exhibit 45: Physician Attrition Patterns by Sex



Source: Model estimates from 2012-2013 bi-annual Florida Physician Licensure Workforce Survey and Centers for Disease Control and Prevention mortality rates by age and sex.

Modeling Hours Worked

Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 Bi-annual Physician Licensure Workforce Survey of physicians in Florida who renewed their license. Analysis of Maryland's physician licensure files found similar work patterns by physician age, sex, and specialty. To generate prediction equations for hours worked patterns by physicians in a specialty, Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable. Explanatory variables included indicators (1=yes, 0=no) for specialty, age group, female, and age-by-female interaction terms. Physicians exhibited hours worked patterns by physician age and sex as illustrated for primary care physicians (Exhibit 39). Young, male physicians tended to work more hours per week than their female counterparts, while the sex gap in hours worked largely disappeared after age 55. Hours worked patterns differed by specialty. Relative to family practice, for example, physicians in nephrology worked 13 hours more per week than dermatologists; cardiologists work 11 hours more and gastroenterologists 10 hours more per week than dermatologists. We defined 1 FTE physician for each specialty as the average hours worked per week in that specialty.

Using data on PAs working at least 20 hours per week, similar regression analyses were conducted using 2013 NCCPA license files to model hours worked patterns of PAs and the 2012 NSSRN to model hours worked patterns for critical care NPs. An FTE was defined for each occupation and specialty as the average hours worked per clinician in that occupation and specialty, using data on clinicians working at least 20 hours per week.

Developing Internal Medicine Subspecialties' Demand Projections

Consistent with the approach adopted for other health professions modeled, the projected demands for internal medicine physicians, and PAs were derived from the common model outlined in Chapter III. Prediction equations for use of office and outpatient services in medical subspecialties were estimated using Poisson regression with 2008-2012 MEPS data. Separate regressions were estimated for children and adults. The dependent variables were annual office visits and annual outpatient visits for each specialty. Explanatory variables consisted of the patient characteristics, socioeconomic and insurance variables, and health status variables described previously. The number of visits by individuals was aggregated using the sample weights in the population file to project future demand in each state.

Prediction equations for hospitalizations and ED visits used a similar approach, namely estimating a logistic regression on 2008-2012 MEPS data. Separate regressions were estimated for children and adults, and for each of the medical conditions categorized in Exhibit 46 (with categories defined by primary ICD-9 diagnosis or procedure codes). The equations predicted probabilities that each individual would have a hospitalization or ED visit for each of the condition categories. While all ED visits were assumed to involve a consultation with an emergency physician, the 2010 NHAMCS is used to identify the probability that another specialty physician provider was seen.

A single logistic regression estimated using the 2010 NHAMCS modeled the probability that an ED visit required a consulting physician. The dependent variable was whether during the visit a second physician was seen. Explanatory variables consisted of patient demographics and insurance type, and indicators variables (1=yes, 0=no) for each condition category. The assumption was made that if a visit required a consult, the consulting physician was in the medical specialty associated with the primary diagnosis code as indicated in Exhibit 46.

Exhibit 46: Hospital Inpatient and Emergency Care Service Demand Drivers by Medical Specialty

Medical Condition	ICD-9 Diagnosis and Procedure Codes	Medical Specialty	Workload Driver Modeled [a]	
			Inpatient Days	Emergency Visits
Allergy & immunology	001-139, 477, 995.3	Allergy & Immunology	Yes	NA
Diseases of the circulatory system	390-459; 745-747; 780, 785	Cardiology	Yes	Yes
NA	All hospitalization	Critical Care	Yes	NA
Diseases of the skin and subcutaneous tissue	680-709; 757; 782	Dermatology	Yes	Yes
Endocrine, nutritional and metabolic diseases, and immunity disorders	240-279; 783	Endocrinology	Yes	Yes
Diseases of the digestive system	520-538; 555-579; 751; 787; 42-54	Gastroenterology	Yes	Yes
Neoplasms, diseases of the blood & blood-forming organs	140-239, 280-289; 790	Hematology/ Oncology	Yes	Yes
Infectious and parasitic diseases	001-139, 477, 40.11, 40.3, 40.9	Infectious Diseases	Yes	Yes
Conditions originating in perinatal period	760-779	Neonatal/ Perinatal Medicine	Yes	Yes
Nephrology	580-589; 55.2-55.8	Nephrology	Yes	Yes
Disease of the respiratory system	460-519;748;786;35-39	Pulmonology	Yes	Yes
Diseases of the musculoskeletal system and connective tissue	725-729	Rheumatology	Yes	Yes

Notes: Analyzed Medical Expenditure Panel Survey (2008-2012) to model annual probability of hospitalization and annual probability of emergency department visit. Analyzed 2012 Nationwide Inpatient Sample to model average length of stay associated with each category of hospitalization. [a] Not all hospital inpatient days within a diagnosis category will necessarily require hospital rounds by a provider in that specialty, and not all emergency visits will require physician consults. NA Not Applicable.

Predicted probabilities were applied on the simulated micro-data set for future years through 2025 to obtain projected service use specific to the settings where these providers work[a]. Demand for cardiologists, for example, was tied to projected demand for ambulatory visits to a cardiologist, inpatient days where the patient's primary diagnosis is cardiology related (of which a portion of days will involve hospital rounds), and emergency department (ED) visits where the patient's primary diagnosis is cardiology related (of which a portion will involve a cardiologist consult).

HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting (Exhibit 24). These ratios were then applied to projections of future demand for services for the Baseline demand scenario in HWSM that assumes the status quo in terms of care use and delivery patterns. Estimated FTE requirements to care for each person were then aggregated to obtain the total demand for physicians.

[a] Due to small sample sizes HWSM does not model profession-setting combinations where service volume is small (e.g., physicians providing care in home health and residential facilities).

Exhibit 47: Physician FTE, Workload, & Staffing by Specialty & Care Delivery Site, 2013

	Office	Outpatient	Inpatient	Emergency
Physician FTE by Care Delivery Site[a]				
Allergy & Immunology	4,480			
Cardiology	16,540	1,070	10,120	210
Critical Care			3,570	
Dermatology	10,340	120	920	
Endocrinology	4,550	170	2,580	140
Gastroenterology	6,250	3,780	3,980	600
Hematology/Oncology	10,010	2,130	3,640	100
Infectious Diseases			8,140	280
Neonatal/Perinatal			4,820	
Nephrology	6,130	1,280	1,790	
Pulmonology	3,100	300	7,900	1,080
Rheumatology	4,540	480	280	170
Physician Workload Measures				
Allergy & Immunology	11,980,000			
Cardiology	29,021,000	1,548,000	20,691,000	3,735,000
Critical Care			183,050,000 [b]	
Dermatology	39,743,000	455,000	2,802,000	
Endocrinology	9,929,000	284,000	4,242,000	2,251,000
Gastroenterology	13,165,000	2,743,000	6,227,000	10,007,000
Hematology/Oncology	25,205,000	3,505,000	5,249,000	1,231,000
Infectious Diseases			8,491,000	4,147,000
Neonatal/Perinatal			25,558,000	
Nephrology	9,250,000	581,000	1,979,000	
Pulmonology	6,821,000	406,000	13,038,000	21,704,000
Rheumatology	7,072,000	221,000	322,000	1,923,000
Physician Staffing Ratios by Care Delivery Site				
Allergy & Immunology	2,674			
Cardiology	1,755	1,447	2,045	17,786
Critical Care			51,275 [a]	
Dermatology	3,844	3,792	3,046	
Endocrinology	2,182	1,671	1,644	16,079
Gastroenterology	2,106	726	1,565	16,678
Hematology/Oncology	2,518	1,646	1,442	12,310
Infectious Diseases			1,043	14,811
Neonatal/Perinatal			5,302	
Nephrology	1,509	454	1,106	
Pulmonology	2,200	1,353	1,650	20,096
Rheumatology	1,558	460	1,150	11,312

Sources: Total physicians based on 2013 AMA Master File. Distributions based on analysis of multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey, 2010 American Board of Internal Medicine survey, specialty-specific surveys and HWSM estimates from MEPS. The proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time. a. totals may not add up to the reported numbers in the brief due to rounding [b] All hospitalizations.

A similar process was used to estimate current and project future demand for PAs. Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each major care delivery setting and specialty. The national percentage of FTE PAs in each setting and specialty, divided by national volume of care in that setting, provided estimates of the portion of an FTE PA per unit of health care service delivered (Exhibit 48). For critical care NP, a general estimate of staffing for all NPs across all medical specialties was applied. This estimate was derived by assuming that NP distribution across settings would reflect the distribution of physicians in all medical specialties by setting.

Exhibit 48: Physician Assistant FTE by Care Delivery Site and Medical Specialty, 2013

Specialty	Provider (FTE)	Workload	Staffing Ratio
Allergy & Immunology	250	11,980,000	47,920
Cardiology	5,480	54,995,000	10,036
Critical Care[a]	2,880	183,050,000	6,067[b]
Dermatology	3,810	43,000,000	11,286
Endocrinology	420	16,706,000	39,776
Gastroenterology	1,560	32,142,000	20,604
Hematology/Oncology	1,940	35,190,000	18,139
Infectious Disease	480	8,491,000	17,690
Neonatal/Perinatal[c]			
Nephrology	370	11,810,000	31,919
Pulmonology	440	41,969,000	95,384
Rheumatology	320	9,538,000	29,806

Source: Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey. [a] Nurse Practitioner. [b] A general estimate of the staffing ratio for all NPs in medical specialties derived by weighting the total number of physician encounters across settings by the proportion of physicians FTEs serving in those setting and dividing that by the total number of NPs practicing in medical specialties in 2013 was applied. [c] Neonatal/Perinatal specialty was not modelled for PAs due to small sample size

The regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus, as well as hours worked based on provider demographics. The demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

C. Surgical Specialty Model

Practitioners considered in this model include physicians and physician assistants (PAs) that cover 10 surgical specialties: general surgery, cardiothoracic surgery, colon/rectal surgery, neurological surgery, ophthalmology, orthopedic surgery, otolaryngology, plastic surgery, urology, and vascular surgery.

Exhibit 49: Summary of Surgical Specialties

Specialty	Description
General Surgery	Focus on organs and other structures in the abdomen.
Cardiothoracic Surgery	Involve operations on the heart, lungs, esophagus, and other organs in the chest.
Colorectal Surgery	Repair damage to the colon, rectum, and anus, caused by diseases of the lower digestive tract, such as cancer and inflammatory bowel disease.
Neurological Surgery	Involve operating on the brain, head, neck, and spinal cord.
Ophthalmology	Concern the full spectrum of eye care, from prescribing glasses and contact lenses to complex eye surgery.
Orthopedic Surgery	Focus on injuries and diseases of the musculoskeletal system including the bones, joints, ligaments, tendons, muscles, and nerves.
Otolaryngology	Focus on the medical and surgical management and treatment of patients with diseases and disorders of the ear, nose, throat, and related structures of the head and neck.
Plastic Surgery	Focus on the repair, reconstruction, or replacement of physical defects involving the skin, musculoskeletal system, maxillofacial structures, hand, extremities, and breast and trunk.
Urology	Involve diagnosis and treatment of diseases of the male and female urinary tracts, as well as the male reproductive organs.
Vascular Surgery	Encompass the diagnosis and management of disorders of the arterial, venous and lymphatic systems, exclusive of the intracranial vessels and the heart.

Estimating the Current Active Workforce Supply

The source for estimating the current active supply of physicians is the 2013 American Medical Association (AMA) Master File Extract. The analysis was limited to active physicians. Because the AMA file is known to misclassify older physicians who have retired as 'active', those over age 75 were deleted from the analysis file. In addition, retired physicians between 50 to 75 years of age were identified and deleted based on predicted probabilities derived from a logistic regression on age and specialty. In addition to adjusting for misclassification of retirees as active physicians, the AMA Masterfile was adjusted for undercounting hospitalists, a large proportion of who are listed under the specialty in which they received their training. The base year counts for PAs come from the 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey.

Modeling New Entrants

The mechanism for adding new entrants to this workforce is done via the creation of a "synthetic" population based on the number and characteristics of recent graduates in each occupation. As described in section II.B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years.

Estimates of total annual new physicians and PAs and the specialty distribution came from multiple sources. The primary sources of data on characteristics of new graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators, the 2013 AMA Masterfile and the American Board of Medical Specialties (ABMS) for physician specialties. Numbers and characteristics of new PAs come from the Physician Assistant Education Association (PAEA) and the NCCPA for physician assistants (Exhibit 50).

Exhibit 50: Age and Sex Distribution of New Physicians by Surgical Specialty

Surgical Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution			
			<25	26-30	31-40	>41
General Surgery	1188	36%	0%	12%	82%	6%
Cardiothoracic Surgery	97	25%	0%	0%	92%	8%
Colon/Rectal Surgery	83	36%	0%	0%	100%	0%
Neurological Surgery	149	17%	0%	5%	87%	8%
Ophthalmology	467	40%	0%	32%	66%	2%
Orthopedic Surgery	1082	11%	0%	2%	94%	4%
Otolaryngology	313	32%	0%	4%	93%	3%
Plastic Surgery	216	29%	0%	2%	93%	5%
Urology	271	25%	0%	4%	95%	1%
Vascular Surgery	122	30%	0%	1%	88%	11%
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%

Source: 2013 AMA Master File, 2012-2013 AAMC GME Census. [a] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs.

Modeling Workforce Attrition

Data sources for modeling attrition patterns of physicians by individual specialty are limited. The primary source of retirement information is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire in the upcoming five years (Exhibit 45). Age-sex specific rates calculated form the Florida Bi-annual Physician Licensure Survey, were combining with the age-sex specific mortality rates to derive the overall attrition rate. Exhibit 45 shows that male and female physicians have similar attrition patterns after adjusting for the slightly higher mortality rates among men. Retirement rates, however, differ by medical specialty. The attrition pattern for PAs was unavailable. As a result, the attrition pattern of family physicians was used as proxy.

Modeling Hours Worked

Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 Bi-annual Physician Licensure Workforce Survey of physicians in Florida who renewed their license. Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable in order to generate prediction equations for hours worked patterns by physicians. Explanatory variables included specialty indicators (1=yes, 0=no), age group, female, and age-by-female interaction terms. Hours worked patterns differed by specialty. Relative to family medicine, for example, physicians in neurological surgery and general surgery work 8 and 7 additional patient care hours more per week. Similar regression analysis was conducted using 2013 NCCPA license files to model hours worked patterns of PAs.

Developing Surgical Subspecialties' Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demand for physicians and PAs was derived from the common model outlined in Chapter III. HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. The consulting physician was in the surgical specialty associated with the primary diagnosis code as indicated in Exhibit 51. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting. These ratios were then applied to projections of future demand for services that assumes the status quo in terms of care use and delivery patterns.

Exhibit 51: Hospital Inpatient and Emergency Care Service Demand Drivers by Surgical Specialty

Surgical Condition	ICD-9 Diagnosis and Procedure Codes	Surgical Specialty	Workload Driver Modeled [a]	
			Inpatient Days	Emergency Visits
General surgery	860-869; 870-904; 925-939; 958-959; 996-999	General Surgery	Yes	Yes
Thoracic surgery	426, 427, 780, 785; 32.6, 34.9, 40.6, 90.4, 35-37	Cardiothoracic Surgery	Yes	NA
Colorectal surgery	17.31-17.36, 17.39, 45.03, 45.26, 45.41, 45.49, 45.52, 45.71-45.76, 45.79, 45.81-45.83, 45.92-45.95, 46.03-46.94, 153-154	Colon/Rectal Surgery	Yes	NA
Neurological surgery	850-854; 950-957; 01.0-05; 89.13	Neurological Surgery	Yes	Yes
Ophthalmology	360-379; 8-16; 95.0-95.4	Ophthalmology	Yes	Yes
Diseases of the musculoskeletal system and connective tissue; injury and poisoning	710-719; 720-724; 730-739; 805-848; 754-756; 76-84	Orthopedic Surgery	Yes	Yes
Otolaryngology	380-389; 744; 18-29	Otolaryngology	Yes	Yes
Plastic surgery	904-949; 749; 18.7, 21.8, 25.59, 26.49, 27.5, 27.69, 29.4, 31.7, 33.4, 46.4, 64.4, 78.4, 81.0-81.99, 82.7, 82.8, 83.8, 85.8, 86.84	Plastic Surgery	Yes	Yes
Diseases of the genitourinary system	590-608; 753; 788; 789; 791; 55-64	Urology	Yes	Yes
Vascular surgery	440-448; 0.4-00.5, 17.5, 35-39	Vascular Surgery	Yes	NA

Notes: Analyzed Medical Expenditure Panel Survey (2008-2012) to model annual probability of hospitalization and annual probability of emergency department visit. Analyzed 2012 Nationwide Inpatient Sample to model average length of stay associated with each category of hospitalization. [a] Not all hospital inpatient days within a diagnosis category will necessarily require hospital rounds by a provider in that specialty, and not all emergency visits will require physician consults.

Exhibit 52: Summary of National FTE Physician Distribution by Care Delivery Site and Surgical Specialty, 2013

	Office	Outpatient	Inpatient Days	Emergency
Physician FTE by Care Delivery Site[a]				
General Surgery	9,740	3,580	14,420	450
Cardiothoracic Surgery	1,050	200	150	3,100
Colon/Rectal Surgery	-	-	1,720	-
Neurological Surgery	-	-	5,110	60
Ophthalmology	16,700	1,650	80	40
Orthopedic Surgery	18,830	2,990	3,010	580
Otolaryngology	7,580	1,470	300	100
Plastic Surgery	4,690	2,400	550	90
Urology	5,750	1,070	2,740	340
Vascular Surgery			3,050	
Physician Workload Measures				
General Surgery	19,207,000	2,459,000	24,367,000	9,511,000
Cardiothoracic Surgery	294,000	19,000	34,000	7,883,000
Colon/Rectal Surgery			24,000	
Neurological Surgery			4,147,000	558,000
Ophthalmology	55,539,000	1,699,000	199,000	1,247,000
Orthopedic Surgery	63,421,000	3,536,000	10,149,000	16,219,000
Otolaryngology	20,816,000	1,201,000	596,000	3,159,000
Plastic Surgery	2,597,000	467,000	267,000	592,000
Urology	19,791,000	1,295,000	8,266,000	11,311,000
Vascular Surgery			1,337,000	
Physician Staffing Ratios by Care Delivery Site				
General Surgery	1,972	687	1,690	21,136
Cardiothoracic Surgery	280	95	227	2,543
Colon/Rectal Surgery			14	
Neurological Surgery			812	9,300
Ophthalmology	3,326	1,030	2,488	31,175
Orthopedic Surgery	3,368	1,183	3,372	27,964
Otolaryngology	2,746	817	1,987	31,590
Plastic Surgery	554	195	485	6,578
Urology	3,442	1,210	3,017	33,268
Vascular Surgery			438	

Sources: Total physicians based on 2013 AMA Master File. Distributions based on HWSM analysis of multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey, specialty-specific surveys. The proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time. [a] totals may not add up to reported totals in the brief due to rounding.

For PAs, a process similar to estimating the physician staffing ratio was used to estimate current and project future FTE demand for PAs (Exhibit 57). Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each major care delivery setting and specialty.

Exhibit 53: Summary of FTE Physician Assistant Distribution by Care Delivery Site and Surgical Specialty, 2013

Surgical Specialty	Physician Assistant (FTE)	Workload	Staffing Ratio
General Surgery	2,960	55,544,000	18,765
Neurological Surgery	2,290	4,705,000	2,055
Ophthalmology	80	58,684,000	733,550
Orthopedic Surgery	10,440	93,325,000	8,939
Otolaryngology	1,020	25,772,000	25,267
Plastic Surgery	730	3,923,000	5,374
Urology	1,610	40,663,000	25,257
Vascular Surgery	1,100	1,337,000	1,215

Source: Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey. PAs were not modeled for cardiothoracic and colon/rectal surgical specialties due to the limited data available for these disciplines.

The regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus, as well as hours worked based on provider demographics. The demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

D. Women's Health Service Provider Model

This section summarizes the methodology for projecting the supply and demand for women's health specialties including obstetrics/gynecology (OB/GYN), certified nurse midwifery (CNMs), and NPs and PAs in women's health. Selected specialties are narrow definitions of women's health that focus on biological aspects of women's health and include reproductive health and preventive care for women.

Estimating the Current Active Workforce Supply

The source for estimating the current active supply of obstetricians/gynecologists (OB/GYNs) is the 2013 American Medical Association (AMA) Master File Extract. The base year counts for APNs and PAs come from the 2013 National Plan and Provider Enumeration System (NPPES) and the 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey. The 2012 Association of Colleges of Nursing (AACN) survey was used to determine the number and age-sex distribution of the APN workforce in women's health, while the 2013 NCCPA professional profile survey was used the determine the age sex distribution of the PA workforce.

Modeling New Entrants

The mechanism for adding new entrants to the workforce each year is the creation of a "synthetic" population of the profession based on the number and characteristics of recent graduates in each occupation. As described in section II.B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years.

Estimates of total annual women's health care providers came from multiple sources. The primary sources of data on characteristics of new graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators, the 2013 AMA Master File and the American Board of Medical Specialties (ABMS) for physician specialties. Numbers and characteristics of new NPs, in the workforce entrants come from the 2012 American Association of Colleges of Nursing (AACN) survey. The 2013 NCCPA Professional Profile is the primary source for characteristics on new PA workforce entrants and the Physician Assistants Education Association the source of data on new PAs trained.

Exhibit 54: Demographics of New Obstetricians/Gynecologists and Nurse Midwives

Women's Health	Annual Graduates	Percent Female	Age Distribution			
			<25	26-30	31-40	>41
Physicians in Obstetrics/Gynecology	1,219	81%	0%	26%	70%	4%
Certified Nurse Midwives	539	100%	2%	23%	31%	44%
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%

Source: 2013 AMA Master File, 2012-2013 AAMC GME, 2012 American Association of Colleges of Nursing (AACN) Survey. [a] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs.

Modeling Workforce Attrition

The primary source of retirement information for physicians in HWSM is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire in the upcoming five years. The Florida survey was used because of its large sample size and detailed information on individual specialties. Attrition patterns for Advanced Practice Nurses (APNs) and PAs were unavailable, so attrition patterns for family physicians were used as proxy for these professions.

Modeling Hours Worked

Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 Bi-annual Physician Licensure Workforce Survey of physicians in Florida who renewed their license. Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable to generate prediction equations for hours worked patterns by physicians. Explanatory variables included specialty indicators (1=yes, 0=no), age group, female, and age-by-female interaction terms. Similar regression analyses were conducted using 2013 NCCPA license files to model hours worked patterns of PAs, and the 2012 National Sample Survey of Nurse Practitioners (NSSNP) for NPs, and the 2006-2012 ACS for CNMs. No sex-by-age interaction terms were included for APNs because the large majority is female.

Modeling Women's Health Care Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demand for physicians, APNs, and PAs was derived from the common model outlined in Chapter III. HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting. These ratios were then applied to projections of future demand for services that assumes the status quo in terms of care use and delivery patterns (Exhibit 55).

For PAs, a process similar to estimating the physician staffing ratio was used to estimate current and project future FTE demand for PAs. Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each women's health service delivery setting and specialty, and the national volume of care in each care setting and specialty, divided by the number of FTE PAs in that setting, provided estimates of PA FTE required per unit of health care service delivered in that setting.

Exhibit 55: Summary of FTE Physician and Physician Assistant in Obstetrics/Gynecology by Care Delivery Site, 2013

Obstetrics/Gynecology	Office	Outpatient	Inpatient	Emergency
FTE by Care Delivery Site				
Physicians	24,620	1,540	15,250	310
Physician Assistant	1,120	540	260	30
Workload Measures				
Physicians	79,807,000	1,493,000	11,208,000	3,327,000
Physician Assistant	79,807,000	1,493,000	11,208,000	0
Staffing Ratios by Care Delivery Site				
Physicians	3,242	969	735	10,732
Physician Assistant	71,256	2,765	43,108	--

Sources: Total physicians based on 2013 AMA Master File. Distributions based on analysis of multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey. Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey. The proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time.

Demand for NPs in women's health and CNMs were tied to the total patient demand for services across settings. This was obtained by dividing the total number of NPs and CNMs by the total number of physician encounters in OB/GYN weighted by the proportion of physician FTEs serving in different settings. The regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus, as well as hours worked based on provider demographics. The demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

Exhibit 56: Summary of Advanced Practice Nurses in Women's Health Care and Workload Measures, 2013

APN Specialty	FTE Number	Total Patient Demand for Services [a, b]	Service-to-APN Ratio
Women's Health Nurse Practitioners	11,940	51,273,000	4,294
Nurse Midwives	11,110	51,273,000	4,615

Notes: [a] Patient demand for services is defined by number of encounters to physician offices, outpatient clinics, inpatient days, and emergency visits weighted by the proportion of FTE physicians delivering care in that setting.
[b]Workload driver is total encounters to offices of obstetricians &gynecologists and total inpatient days for child birth.

E. Other Medical Specialties:

This section summarizes the methodology for projecting the national supply and demand for physicians and non-physician providers: Physician Assistants (PAs) and Certified Registered Nurse Anesthetists (CRNAs) in Anesthesiology, Emergency Medicine, Neurology and Physical Medicine and Rehabilitation.

Estimating the Current Active Workforce Supply

The primary source for estimates of physicians currently active in the above-mentioned specialties is the 2013 American Medical Association (AMA) Master File Extract. The analysis was limited to active physicians under age 75. Physician specialty was identified by using the 2013 AMA Masterfile along with the American Board of Medical Specialties (ABMS) file on physician specialties. The base year counts for CRNAs come from the 2013 National Plan and Provider Enumeration System (NPPES), while the age-sex distribution came from the 2013 ACS. The 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey was utilized to develop the base year counts and age-sex characteristics for PAs practicing in Anesthesiology, Emergency Medicine, Neurology and Physical Medicine and Rehabilitation.

Modeling New Entrants

The primary sources of data on characteristics of physician graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators. New physician graduates were assigned to Anesthesiology according to the base year proportions reported in the 2013 AMA Master File from the American Board of Medical Specialties (ABMS). Numbers and characteristics of new CRNA came from the 2012 American Association of Colleges of Nursing (AACN) survey. The Physician Assistants Education Association data were used to determine the number of new PAs trained. The 2013 NCCPA Professional Profile was used to determine the characteristics of the new PAs assuming that the distribution of PAs by different characteristics would remain the same as in the current workforce. Regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus.

Exhibit 57: Age and Sex Distribution of New Physicians, APNs and PAs

Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution			
			<25	26-30	31-40	>41
Physician Specialties						
Anesthesiology	2,174	36%	0%	18%	76%	6%
Emergency Medicine	1,754	40%	0%	35%	61%	4%
Neurology	687	44%	0%	10%	77%	13%
Physical Medicine & Rehabilitation	434	37%	0%	10%	81%	9%
Advanced Practice Nurses & Physician Assts.						
Certified Registered Nurse Anesthetist	2,493	58%	2%	40%	37%	23%
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%

2013 AMA Master File, 2012-2013 AAMC GME Census, 2012 American Association of Colleges of Nursing (AACN) survey, 2013 NCCPA Professional Profile, Physician Assistance Education Association. [b] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs.

Modeling Workforce Attrition

As in the case of other specialties, physician retirement rates were calculated from the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire. This data was compared to the AAMC's 2006 Survey of Physicians over Age 50 which collected information on age at retirement or age expecting to retire. Both sources showed similar retirement rates. However, the Florida survey had a larger sample size and more detailed individual specialties. Retirement rates were combined with the age-sex specific mortality rates adjusted downward to reflect the lower mortality of healthcare workers.[10] Emergency medicine, anesthesiology, and radiology showed earlier retirement rates compared to physicians in other specialties. Attrition pattern for family physicians was used as proxy for attrition rates of PAs and CRNAs.

Modeling Hours Worked

Ordinary Least Squares regressions were conducted for each occupation using reported average hours worked per week as the dependent variable and age group, sex and age-sex interaction as explanatory variables. For physicians, data from the Florida 2012-2013 bi-annual Physician Licensure Workforce Survey (n=18,016) file of physicians was used. Hours worked patterns differed by specialty. An FTE was defined for each specialty as the average number of patient care hours worked in that specialty.

Similar regression analyses were conducted using 2013 NCCPA Professional Profile Survey to model hours worked patterns of PAs and the 2006-2012 ACS to model hours worked patterns of CRNAs. An FTE was defined for each occupation as the average hours worked per clinician in that occupation and specialty, using data on clinicians working at least 20 hours per week.

Modeling Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demand for physicians, CRNAs and PAs was derived by applying the predicted probabilities for each demographic group estimated from MEPS data on the simulated micro-data set for future years derived from the Census Bureau to obtain projected service use specific to the settings where these providers work. Using logistic regression, and the appropriate ICD9 codes (320-359, 742, 781, 784, 800-804 for neurology; 0.4-00.5, 17.5, 35-39; 93 for Physical Medicine and Rehabilitation services), prediction equations for office visits, inpatient days and emergency room visits for each type of provider were developed with 2008-2012 MEPS data. Separate regressions were estimated for children and adults

Prediction equations for ED visits used a similar approach, but did not use ICD9 codes. Instead, all ED visits were assumed to involve a consultation with an emergency physician. Because MEPS lists only the highest level of provider seen, the 2010 NHAMCS is used to identify the probability that a PA was also seen. Provider demand in anesthesiology was determined by the demand for all surgical procedures across all settings. The predicted probabilities of service use by demographic groups when applied to the future population predicted the workload of the different occupations.

Exhibit 58 provides the staffing ratio for each type of service was derived by dividing the current volume of services by the number of provider FTE who currently provide these services and applied to the projected service demand to obtain the predicted demand for provider FTE.

Exhibit 58: Summary of FTE Physician Distribution by Care Delivery Site, 2013

	Office	Outpatient	Inpatient	Emergency	Other[a]	Total
Workload Measures						
Anesthesiology [b]						21,205885
Emergency Medicine				118,570,000		
Neurology	13,996,000	642,000	3,139,000	5,233,000	316,439,000	
Physical Medicine and Rehabilitation	3,307,000	326,000	621,000		316,439,000	
Physician Distribution by Care Delivery Site in FTE						
Anesthesiology						45,940
Emergency Medicine				39,340		39,340
Neurology	10,630	1,720	3,270	490		16,110
Physical Medicine and Rehabilitation	8,430	830	1,580			10,840
Physician Staffing Ratios						
Anesthesiology						462
Emergency Medicine				3,014		
Neurology	1,317	373	960	10,680		
Physical Medicine and Rehabilitation	392	393	393			
Physician Assistant Distribution by Care Delivery Site						
Anesthesiology						750
Emergency Medicine				13,800		
Neurology	430	220	200		20	870
Physical Medicine & Rehabilitation	510	150	100		170	930
Physician Assistant Staffing Ratio						
Anesthesiology						28,274
Emergency Medicine				11,917		
Neurology	32,549	2,918	15,695		15,821,000	
Physical Medicine & Rehabilitation	6,484	2,173	6,210		1,861,405	
Nurse Anesthetists						44,660
Nurse Anesthetist Staffing Ratio						474

Source: 2013 AMA Masterfile, 2013 National Plan and Provider Enumeration System (NPPES) and 2013 NCCPA Professional Profile, Physician Assistance Education Association; [a] Other category includes long term care, school health, home and hospice, and all other settings; Workload driver is the size of the population. [b] Workload driver is defined by the total outpatient and inpatient surgical procedures.

The regional provider demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

XI. HWSM Improvement, Validation, Strengths, and Limitations

This chapter summarizes activities undertaken to improve and validate HWSM and discusses the strengths and limitations of the model.

A. HWSM Improvement

To provide the highest quality projections, questions regarding technical accuracy and suggestions for improvement of the model are thoroughly investigated. In 2019, in response to questions regarding existence of overdispersion in the Poisson models of number of annual visits to various types of providers, we investigated the issue, including potential alternative models. If data are distributed according to a Poisson distribution, their mean will equal their variance. However, the MEPS data regarding number of annual visits to various provider type/specialties tend to contain more zeroes than would be expected in a Poisson distribution, thus leaving the mean of the data substantially less than their variance (or, alternatively, producing variance/dispersion too large relative to the mean). Fitting a Poisson model to data exhibiting overdispersion will tend to produce understated standard errors.

Potentially better fitting models for count data containing more zeroes than would expected in a Poisson regression include negative binomial, zero-inflated, and zero-altered models. In the zero-inflated and zero-altered models, data are generated in a two-stage process. Some data are restricted to always be zero by one data-generation process, and a separate process for non-"certain zero" observations produces typical count data. For number of annual visits to a healthcare provider, some observations will be "certain zeroes" (i.e. for people without access due to lack of resources or insurance, or with low health literacy, etc.); for people with access, the number of annual visits will be 0, 1, 2, 3, etc. [Note that zero-altered models restrict the observations for the non-"certain zeroes" to be non-negative; since people with access often choose not to seek care from a particular type of provider in a given year, zero-altered models were eliminated from consideration.]

The predictions of negative binomial (NB), zero-inflated Poisson (ZIP), and zero-inflated negative binomial (ZINB) were compared for models of annual visits to several healthcare specialties. Overall, the ZINB model performed slightly better than the other models in terms of small mean squared error. However, as had been reported by others in online forums who both developed and used these zero-inflated, the estimation algorithms failed to converge in some cases. Since the zero-inflated models were not estimable for all specialties, to keep the model consistent across all provider specialties, the negative binomial model ultimately was chosen to replace the Poisson model.

Also, in 2019, the suggestion to use dental insurance in place of medical insurance as a predictor in the regressions for number of annual visits to oral healthcare providers was evaluated. When employing, alternately, medical insurance and dental insurance as predictors of dental visits in the full model, the root mean square error (RMSA) -- a measure of accuracy of the resulting predictions – was equivalent to two decimal places for the two formulations in regressions of visits to both dentists and hygienists.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

where y_j = observed visits, and $\hat{y}_j$ = visits predicted by the model, for each observation j.

Additional comparisons were performed, as follows. The data were split 10 times for each oral health professional designation into training sets (75%, picked randomly) and testing set (other 25%). In each split (and for each profession), the percentage of total prediction error using the medical insurance coverage variable was compared to the percentage of total prediction error using the dental insurance coverage variable. Total prediction error was sometimes higher for the model with dental insurance, sometimes higher for the model with medical insurance, but always within 0.5% of each other. Thus, no compelling evidence was found to recommend one insurance variable over another. As such, the medical insurance predictor variable was retained in predicting annual visits to oral healthcare providers, to maintain consistency among regression models of number of annual visits to all healthcare-related professions.

B. HWSM Validation

A model, by definition, is a simplified version of reality. Validation activities are important to help ensure that the model reflects reality as accurately as possible. Validation of HWSM is a continual process. As different health professionals are accommodated and the model is updated with the new data, validation activities will continue.

Following International Society for Pharmacoeconomics and Outcomes Research (ISPOR) guidelines on best practices, validation activities in HWSM included the following:[a]

- **Review by subject matter experts (face validity)**. The model framework should conform to observations about how the system works, and be consistent with theory. Expert review also helps ensure that the model uses the best available inputs and parameters. Model outputs should be consistent with expectations of subject matter experts.

  The model framework was approved by a technical evaluation panel consisting of experts in health care workforce at HRSA. The modeling approach was selected because it is particularly useful for analyzing complex systems such as the health care system, where decision-making is decentralized and autonomous. For supply modeling, each individual makes his or her career and labor force participation decisions based on their own unique characteristics and in response to external factors such as earnings potential and unemployment risks. For demand modeling, decisions to use health care services are made by individuals depending upon their health risks and financial constraints. HWSM has the potential to capture the complex dynamic interactive processes that characterize the demand for and supply of health care providers.

  The model makes use of the most recent data available to date and can be updated with new data as they become available without changing the basic features of the model.

  The outputs from the nursing model have been verified by an established researcher in the area of health workforce.[b]

- **Internal validation (verification)**. This set of activities involved reviewing computer code for accuracy, validating parameters in the model against their source, and putting HWSM through a "stress test" by modeling extreme input values to test whether the model produces expected results.

  Internal validation activities have been conducted on all parts of the model used to forecast supply and demand for oral health, nursing, and the cross-occupation professions. Regression coefficients were examined to flag unrealistic estimates and results were examined to ensure that state-level estimates add up to national estimates.

[a] Eddy DM, Hollingworth W, Caro JJ, Tsevat J, McDonald KM, Wong JB. 2012."Model transparency and validation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force—7." *Value Health*;15(6):843-850.

[b] Personal communication, Dr. Thomas Ricketts.

- **External and predictive validation**. This form of validation was used to identify external data sources (not used in model development) for comparison to model outputs.

  As an example, the health-related characteristics of the baseline population data base created in HWSM were calibrated by comparing the prevalence estimates to published U.S. Centers for Medicare and Medicaid Services (CMS) and the most recent American Health Care Association (AHCA) resident counts in each state. Similarly, the expected numbers of home health visits generated by HWSM were compared to the results from the latest version of the National Home and Hospice Care Survey (NHHCS). Validation and calibration activities were conducted on the labor force participation rates which included developing preliminary supply projections to determine if the base year age distribution of the workforce was consistent with labor force attrition patterns. In addition, information from occupational associations and other sources were used to validate the model inputs.

- **Between-model validation (cross validation)**. This type of validation compared model outputs with results of other models.

  The cross-model comparisons made thus far have compared HWSM projections with the BLS 10-year (2012 to 2022) employment forecasts for select occupations. The BLS forecasts are based on two major components: (1) employment opportunities due to demand growth; and, (2) employment needs to replace people who have left the labor force. HWSM produces similar outputs. HWSM and BLS projections are relatively similar despite using very different modeling approaches, data, and assumptions. Results from published articles[148,149] on nursing supply were also used to validate HWSM projections on the nursing workforce

C. HWSM Strengths and Limitations

The main strengths of HWSM are the use of recent data sources and a sophisticated microsimulation model for projecting health workforce supply and demand. Compared to population-based approaches, this approach has a number of advantages:

- More predictive variables can be used in modeling, which enhances the accuracy of results.
- Lower levels of geography can be modeled, which meets HRSA's goal of building more accurate state level projections.
- Projection models can be easily consolidated across occupations, with profession-specific equations integrated into a single platform.

- The modular approach in HWSM allows for refinements and improvements to be carried out in sub-components of the model.

HWSM uses individuals as the unit of analysis. This level of analysis creates flexibility for incorporating changing prevalence of certain chronic conditions or health-related behaviors and risk factors into demand estimations. HWSM also provides added flexibility for modeling the workforce implications of changes in policy (such as expanded health insurance coverage under the ACA).

Many of the limitations of HWSM stem from current data limitations. For example, HWSM uses the ACS to estimate current supply of many health occupations, although many states have access to more complete supply data collected through the licensure/certification processes. On the demand side, one limitation of the BRFSS as a data source is that as a telephone-based survey, it tends to exclude people who may not have their own telephone.

Other current data limitations associated with HWSM include the following:

1. There is little information on the influence of provider and payer networks on demand and consumer care migration patterns.
2. Data are currently lacking to estimate demand and adequacy of supply at the state and sub-state levels for many health occupations. While the ACS is available as a substitute for detailed demographic information, it is unable to identify occupations to the six-digit Standard Occupational Classification level. Furthermore, counts of the current level of an occupation are more precise when taken from licensing data instead of estimates from either the ACS or the OES.
3. On the demand side, there is a paucity of information on how care delivery patterns might change over time in response to the ACA and other emerging market factors.
4. Due to lack of data, it is not possible to identify services received in certain specialized settings such as ambulatory surgical units.

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XIII. Appendix

Exhibit A-1: Summary of Workload Measures and Staffing Ratios for Select Allied Health Occupations

Occupation	*Total*	*Ambulatory*	*Inpatient*	*Home Health*	*Nursing Home/Residential Care*	*School Health*	*Academia*	*Other*
Diagnostic Services								
Diagnostic medical sonographers	100% (65,790)	37% (24,240)	61% (40,070)					2% (1,480)
Medical and clinical laboratory technologists	100% (166,730)	35% (59,070)	51% (85,310)		<1% (830)		4% (7,440)	8% (14,090)
Medical and clinical laboratory technicians	100% (160,190)	35% (56,750)	51% (81,960)		<1% (800)		4% (7,150)	8% (13,540)
Nuclear medicine technologists	100% (19,650)	24% (4,630)	74% (14,520)					3% (500)
Radiologic technologists	100% (200,650)	34% (69,550)	60% (121,080)					5% (10,020)
Dietary and Nutrition Services								
Registered dietitians	100% (78,970)	19% (14,700)	35% (27,500)		15% (11,610)	10% (7,630)		22% (17,530)
Dietetic technicians	100% 32,240	3% 880	41% 13,060		41% 13,300	3% 1,110		12% 3,880
Pharmacy Services								
Pharmacists	100% (302,600)	62% (188,890)	28% (85,970)		<1% (1,340)	<1% (50)		9% (26,350)
Pharmacy technicians	100% (398,390)	79% (314,760)	16% (63,410)		<1% 710			5% 19,510
Pharmacy aides	100% (36,660)	89% (32,500)	8% (2,860)					4% (1,310)
Rehabilitation Services								
Occupational therapists	100% (104,290)	29% (30,740)	27% (28,620)	6% (6,680)	17% (17,270)	15% (15,960)		5% (5,020)
Physical therapists	100% (237,560)	45% (107,390)	30% (70,790)	9% (20,570)	9% (21,670)	3% (7,900)		4% (9,240)
Occupational therapy assistants	100% (38,170)	47% (18,070)	16% (6,010)	7% 2,690	21% (7,980)	5% (1,990)		4% (1,420)

Occupational therapy aides	100% (7,210)	49% (3,520)	24% (1,760)	5% 330	14% 1,040	3% 240		4% 320
Physical therapy assistants	100% (85,580)	53% (45,130)	22% (19,180)	9% (7,900)	12% (10,640)	1% 640		2% 2,100
Physical therapy aides	100% (50,030)	66% (33,030)	23% (11,390)	1% (580)	6% (3,020)	<1% 110		4% 1,910
Therapeutic & Respiratory Services								
Respiratory therapists	100% (111,210)	2% (2,750)	91% (101,740)	2% (1,860)	2% (2,160)	<1% (20)		2% (2,680)
Chiropractor	100% (57,470)	99% (56,720)	<1% (260)		<1% (60)			<1% (430)
Podiatrists	100% (18,160)	91% (16,440)	8% (1,410)		<1% (10)			2% (300)
Radiation therapists	100% (19,700)	24% (4,780)	70% (13,770)		1% (130)	<1% (50)		5% (970)
Vision and Hearing Services								
Optometrist	100% (42,680)	88% (37,400)	4% (1,600)					9% (3,680)
Audiologist	100% (14,380)	53% (7,660)	25% (3,530)		<1% (20)	8% (1,190)		14% (1,980)
Opticians	100% (61,640)	95% (58,380)	2% (1,330)		<1% (50)			3% (1,890)
Community Health Workers								
Community health workers	100% (51,900)	21% (10,740)	11% (5,450)	19% (9,610)	5% (2,520)	2% 890	2% (1,040)	42% (21,650)

Notes: Standardized FTE definition, 1 FTE= 40 hours/week. * Numbers might not sum to totals due to rounding.

Source: American Community Survey, 2012-2016 5-year file, 2016 & 2017 BLS OES Survey

Health Workforce Workload by Care Delivery Site							
	Delivery Sites (Units)						
Occupation	***Ambulatory (Visits)***	***Inpatient (Days)***	***Home Health (Visits)***	***Nursing Home/Residential Care (Population)***	***School Health (Population)***	***Academia (Population)***	***Other (Population)***
Diagnostic medical sonographers	1,101,018,005	146,077,053					323,127,515
Medical and clinical laboratory technologists	1,101,018,005	146,077,053		2,009,410		35,800,450	323,127,515
Medical and clinical laboratory technicians	1,101,018,005	146,077,053		2,009,410		35,800,450	323,127,515
Nuclear medicine technologists	6,237,619	34,684					323,127,515
Radiologic technologists	6,237,619	34,684					323,127,515
Registered dietitians	1,101,018,005	146,077,053		2,009,410	53,825,270		323,127,515
Dietetic technicians	1,101,018,005	146,077,053		2,009,410	53,825,270		323,127,515
Pharmacists	3,468,554,358	146,077,053		2,009,410	53,825,270		323,127,515
Pharmacy technicians	3,468,554,358	146,077,053		2,009,410	53,825,270		323,127,515
Pharmacy aides	3,468,554,358	146,077,053		2,009,410	53,825,270		323,127,515
Occupational therapists	9,646,726	5,612,502	650,940	2,009,410	53,825,270		323,127,515
Physical therapists	102,513,485	5,612,502	895,305	2,009,410	53,825,270		323,127,515
Occupational therapy assistants	9,646,726	5,612,502	650,940	2,009,410	53,825,270		323,127,515
Occupational therapy aides	9,646,726	5,612,502	650,940	2,009,410	53,825,270		323,127,515
Physical therapy assistants	102,513,485	5,612,502	895,305	2,009,410	53,825,270		323,127,515
Physical therapy aides	102,513,485	5,612,502	895,305	2,009,410	53,825,270		323,127,515
Respiratory therapists	8,736,958	12,495,136	22,186,027	2,009,410	53,825,270		323,127,515
Chiropractor	107,171,107	5,612,502		2,009,410			323,127,515
Podiatrists	10,641,001	5,612,502		2,009,410			323,127,515

Health Workforce Workload by Care Delivery Site							
	Delivery Sites (Units)						
Occupation	***Ambulatory (Visits)***	***Inpatient (Days)***	***Home Health (Visits)***	***Nursing Home/Residential Care (Population)***	***School Health (Population)***	***Academia (Population)***	***Other (Population)***
Radiation therapists	31,839,941	34,684		2,009,410	53,825,270		323,127,515
Optometrist	21,560,985	2,271,503					323,127,515
Audiologist	26,307,724	581,036		2,009,410	53,825,270		323,127,515
Opticians	21,560,985	2,271,503					323,127,515
Community health workers	16,444,489	146,077,053	943,483	2,009,410	53,825,270	35,800,450	323,127,515

Source: 2016 HWSM baseline results

Health Workforce Staffing Ratios by Care Delivery Site							
	Delivery Sites (Units per Provider)						
Occupation	*Ambulatory (Visits)*	*Inpatient (Days)*	*Home Health (Visits)*	*Nursing Home/Residential Care (Population)*	*School Health (Population)*	*Academia (Population)*	*Other (Population)*
Diagnostic medical sonographers	45,423	3,646					217,888
Medical and clinical laboratory technologists	18,640	1,712		2,430		4,814	22,936
Medical and clinical laboratory technicians	19,401	1,782		2,528		5,011	23,872
Nuclear medicine technologists	1,347	2					648,850
Radiologic technologists	90	0.3					32,242
Registered dietitians	74,899	5,313		173	7,052		18,435
Dietetic technicians	1,252,580	11,183		151	48,448		
Pharmacist	18,363	1,699		1,503	1,055,397		12,262
Pharmacy technicians	11,020	2,304		2,846			16,560
Pharmacy aides	106,721	51,165					247,607
Occupational therapists	314	196	98	116	3,372		64,330
Physical therapists	955	79	44	93	6,818		34,971
Occupational therapy assistants	534	934	242	252	27,061		227,555
Occupational therapy aides	2,740	3,187	1,997	1,927	222,418		1,019,330
Physical therapy assistants	2,272	293	113	189	84,631		154,017
Physical therapy aides	3,104	493	1,546	666	480,583		169,354
Respiratory therapists	3,177	123	11,915	930	3,166,192		120,570
Chiropractor	1,889	21,422		35,882			746,253
Podiatrists	647	3,980		154,570			1,095,348

Health Workforce Staffing Ratios by Care Delivery Site							
	Delivery Sites (Units per Provider)						
Occupation	***Ambulatory (Visits)***	***Inpatient (Days)***	***Home Health (Visits)***	***Nursing Home/Residential Care (Population)***	***School Health (Population)***	***Academia (Population)***	***Other (Population)***
Radiation therapists	6,661	3		15,223	1,196,117		332,436
Optometrist	576	105					87,806
Audiologist	3,435	165		91,337	45,193		162,867
Opticians	369	126		43,122			171,128
Community health workers	1,531	26,803	98	797	60,410	34,324	14,927

Source: 2012-2016 5-year American Community Survey, 2016 & 2017 BLS OES Survey and HWSM baseline results