Health Workforce Model Documentation

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Prepared by:

Tim Dall

Terry West

Ritashree Chakrabarti

Will Iacobucci

April Semilla

Alpana Hansaria

IHS Inc.

1150 Connecticut Ave, NW | Suite 401 | Washington, D.C. 20036

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ACRONYMS USED IN REPORT

AACN	American Association of Colleges of Nursing
ACS	American Community Survey
ADA	American Dental Association
AMA	American Medical Association
APRN	Advanced practice nurse
BLS	Bureau of Labor Statistics
BRFSS	Behavioral Risk Factor Surveillance System
CDC	Centers for Disease Control and Prevention
CMS	Centers for Medicare and Medicaid Services
DPMM	IHS Disease Prevention Microsimulation Model
HDMM	IHS Healthcare Demand Microsimulation Model
HRSA	Health Resources and Services Administration
HWSM	IHS Health Workforce Supply Model
IPEDS	Integrated Postsecondary Education Data System
LPN/LVN	Licensed practical/vocational nurse
MEPS	Medical Expenditure Panel Survey
NAMCS	National Ambulatory Medical Care Survey
NCLEX	National Council Licensure Examination
NCSBN	National Council of State Boards of Nursing
NCCPA	National Commission on Certification of Physician Assistants
NHAMCS	National Hospital Ambulatory Medical Care Survey
NIS	Nationwide Inpatient Sample
NLN	National League for Nursing
NNHS	National Nursing Home Survey
NP	Nurse practitioner
NSSNP	National Sample Survey of Nurse Practitioners
PA	Physician assistant
RN	Registered nurse
SNF	Skilled Nursing Facility

I. INTRODUCTION

This report provides technical documentation of the health workforce microsimulation models developed by IHS Inc., with contributions to the model development from the Center for Health Workforce Studies (SUNY-Albany) and the various organizations for which studies have been conducted using these models. We provide background information and an overview of the workforce models. Then, we document the data, methods, assumptions and inputs for the demand model—referred to as the Health Care Demand Microsimulation Model (HDMM). We then document the supply model—referred to as the Health Workforce Supply Model (HWSM). The next section provides a brief overview of IHS's Disease Prevention Microsimulation Model (DPMM) used to model the workforce implications of strategies to prevent or manage chronic disease.[1] The final section describes work to validate the model, model strengths and limitations, and areas of ongoing and future research.

The models continue to be maintained as new data and research becomes available, with additional modules and scenario modeling capabilities developed and refinements made. This documentation is intended to help make the models transparent and provide researchers and stakeholders the opportunity to provide feedback for improving the models. This report is updated periodically to reflect refinements to the models and updated data sources. Hence, application of the model to previous studies might have used earlier data sources than documented in this report.

Background

The workforce models described here are unique in their approach, breadth and complexity. Health workforce projection models have been used for decades to assist with workforce planning and to assess whether the workforce was sufficient to meet current and projected future demand (or need) at the local, regional, state, and national levels. The models described here use a microsimulation approach where individual people (patients and clinicians) are the unit of analysis. While microsimulation models have been used to study complex issues on a variety of topics[2], this is the first broad application of microsimulation modeling for developing health workforce projections.

Approaches used historically in the U.S. to model the demand for health workers include: (1) convening expert panels that consider patient epidemiological needs and provider productivity;[3] (2) extrapolating care use and delivery patterns from beneficiaries in health maintenance organizations;[4] (3) extrapolating trends based on the correlation between physicians-per-population and gross domestic product per capita;[5] and (4) developing demand models that use historical patterns of health care use and delivery to create detailed provider-to-population ratios.[6] Such "macrosimulation" approaches that model demand at the population

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[1] More detailed documentation of the Disease Prevention Microsimulation Model is available elsewhere. https://www.ihs.com/products/healthcare-modeling.html

[2] See, for example, the Transfer Income Model, version 3 (TRIM3) that simulates the major governmental tax, transfer, and health programs and is used to inform policy planning and evaluation. http://trim3.urban.org/T3Welcome.php

[3] Reinhardt UE. The GMENAC Forecast: an Alternative View. *Am.J.Public Health* 71, no. 10 (1981): 1149-1157.

A. R. Tarlov. Response to GMENAC Report. *J.Indiana State Med.Assoc*. 74, no. 12 (1981): 772.

[4] Weiner JP. Forecasting the Effects of Health Reform on US Physician Workforce Requirement. Evidence From HMO Staffing Patterns. *JAMA* 272, no. 3 (1994): 222-230.

Weiner JP. Prepaid Group Practice Staffing and U.S. Physician Supply: Lessons for Workforce Policy. *Health Aff*. Suppl Web Exclusives (2004): W4-59.

[5] Cooper RA et al. Economic and Demographic Trends Signal an Impending Physician Shortage. *Health Aff*. 21, no. 1 (2002): 140-154.

[6] Association of American Medical Colleges. The Complexities of Physician Supply and Demand: Projections Through 2025. 2011

U.S.Department of Health and Human Services. The Physician Workforce: Projections and Research into Current Issues Affecting Supply and Demand. 2011 level have limited ability to model policy changes or paradigm shifts in care delivery because most coverage and treatment decisions are determined by individual circumstances. While approaches used historically for modeling demand vary widely, the approach to model supply has been relatively similar across studies and models the likely workforce decisions of provider cohorts as they entered and progressed through their career. Similar modeling approaches have been used across health professions.

Modeling approaches used in the past faced many challenges—data limitations, computing resources, and gaps in research and understanding of health workforce issues. The use of microsimulation modeling to study the health care system was proposed in the early 1970s by Yett and colleagues, but data and computer computational constraints prevented the full implementation of such a model.[7] Improved computing power and wider access to data and research have enabled development of more sophisticated workforce models that presumably can provide more accurate projections and that can be forward looking in terms of a changing health care delivery and policy landscape. The microsimulation models described here were designed to help address limitations of earlier models.

The workforce models described here have been adapted to model national, state and local area supply and demand for many organizations. These include:

- Federal Bureau of Health Workforce (to model physicians, advanced practice nurses, physician assistants, nurses, oral health providers, behavioral health providers, and other health occupations such as therapists and technicians) at the national and state level.[8]
- States—including Arkansas (primary care providers), Florida (physicians), Georgia (nurses, physicians, and physician assistants), Hawaii (multiple occupations), Maryland (select physician specialties), New York (multiple occupations), South Carolina (multiple occupations), and Texas (nurses).[9]
- Trade and professional associations. [10]
- Hospitals and health systems—including market assessment and regional planning, and the workforce implications of strategies to restructure the healthcare delivery system.

The DPMM, which models strategies to prevent or manage chronic disease and the resulting implications for health care use and provider demand, has also been used for work with:

- Life sciences companies to model burden of disease and strategies to prevent or delay onset of diabetes, cardiovascular disease and other chronic conditions associated with obesity.[11]

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[7] Yett DE, Drabek L, Intriligator MD, Kimbell LJ. A Microeconomic Model of the Health Care System in the United States. Annals of Economic and Social Measurement. April 1975. pp. 407-433.

[8] See various reports published at http://bhpr.hrsa.gov/healthworkforce/supplydemand/index.html

[9] *Florida Statewide and Regional Physician Workforce A: Estimating Current and Forecasting Future Supply and Demand*. Prepared for the Safety Net Hospital Alliance of Florida. 2015. http://safetynetsflorida.org/wp-content/uploads/Jan-28-IHS-Report-PDF.pdf

The Primary Care Workforce in Arkansas: Current and Future Supply and Demand. http://www.achi.net/Content/Documents/ResourceRenderer.ashx?ID=206

[10] *The Complexities of Physician Supply and Demand: Projections from 2013 to 2025.* Prepared for the Association of American Medical Colleges. Washington, DC: Association of American Medical Colleges; 2015. https://www.aamc.org/download/426242/data/ihsreportdownload.pdf

Dall TM, Gallo PD, Chakrabarti R, West T, Semilla AP, Storm, MV. An Aging Population and Growing Disease Burden Will Require a Large and Specialized Health Care Workforce by 2025. *Health Affairs*. 2013; 32:2013-2020.

Dall TM, Chakrabarti R, Storm MV, Elwell EC, and Rayburn WF. Estimated Demand for Women's Health Services by 2020. *Journal of Women's Health*. 2013; 22(7): 643-8.

Dall TM, Storm MV, and Chakrabarti R. Supply and demand analysis of the current and future US neurology workforce. *Neurology*. 2013; 81(5): 470-478.

[11] Su W, Huang J, Chen F, Iacobucci W, Dall TM, Perreault L. Return on Investment for Digital Behavioral Counseling in Patients with Prediabetes and Cardiovascular Disease. Preventing Chronic Disease. 2016; 13; ;150357.

- Trade associations and non-profit organizations to model burden of chronic disease and strategies to reduce future burden including lifestyle interventions to promote improved diet and increased physical activity, smoking cessation programs, improved screening and treatment, and improved medication adherence (to control blood pressure, cholesterol, and blood glucose levels).[12]

The goals behind development and maintenance of these microsimulation models include ability to:

1. Provide the most accurate workforce supply and demand projections possible, and provide timely updates to reflect the latest data, trends, policies, and research in the field.
2. Inform strategies and policy decisions with health workforce implications.
3. Integrate supply and demand across many occupations and specialties into a dynamic model.
4. Adapt the model to state and sub-state levels.

Health Workforce Model Overview

To provide maximum flexibility for adapting the model to different populations and to unique supply and demand scenarios, these models use a microsimulation approach. As depicted in Exhibit 1, there are three major modeling components: (1) modeling demand, (2) modeling supply, and (3) modeling care delivery. Consistent with recommended standards we developed self-contained modules that describe different components of the health care system.[13]

1. **Demand:** The Healthcare Demand Microsimulation Model has three major components: (a) characteristics of each person in a representative sample of the current and future population (demographics, socioeconomics, health-related behavior, presence of chronic conditions, insurance, etc.), (b) health care use patterns that relate patient characteristics to annual use of health care services by delivery setting and medical condition/provider specialty, and (c) staffing patterns that translate demand for health care services into requirements for full time equivalent (FTE) providers by occupation/specialty and by care delivery setting. Health care use and staffing patterns are influenced by changing demographics and trends in care reimbursement and delivery.
2. **Supply**: The Health Workforce Simulation Model simulates workforce decisions for each individual provider based on his or her demographics, profession and specialty, and characteristics of the local or national economy and labor market. Components include: (a) characteristics of the starting supply, (b) characteristics of new entrants to the workforce, (c) attrition (from retirement, death, or move out of the geographic area of interest), and (d) work patterns.
3. **Disease management:** The Disease Prevention Microsimulation Model simulates treatment/intervention scenarios to quantify their impact on preventing or delaying onset of chronic disease and sequelae.

Su W, Huang J, Chen F, Iacobucci W, Mocarski M, Dall TM, Perreault L. Modeling the Clinical and Economic Implications of Obesity using Microsimulation. *Journal of Medical Economics*. 2015: 1-12.

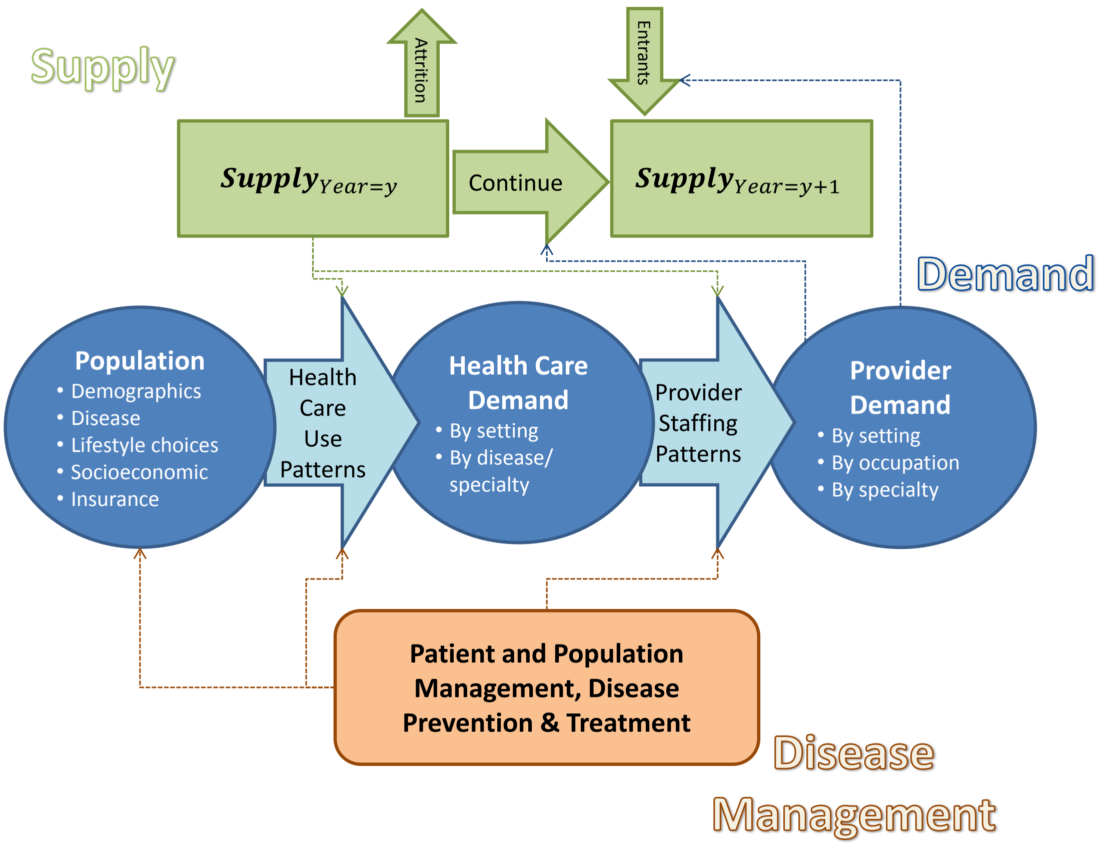
Dall TM, Storm MV, Semilla AP, Wintfeld N, O'Grady M, and Narayan VKM. Value of Lifestyle Intervention to Prevent Diabetes and Sequelae. *American Journal of Preventive Medicine*. 2015 Mar;48(3):271-280.

[12] Semilla AP, Chen F, and Dall TM. Reductions in Mortality Among Medicare Beneficiaries Following the Implementation of Medicare Part D. *American Journal of Managed Care*. 2015 Jul; 21(9)S165-171.

[13] Citro CF and Hanushek EA. *Improving Information for Social Policy Decisions: The Uses of Microsimulation Modeling – Volume I: Review and Recommendations*. Washington, DC: National Academy Press, 1991, 360 pages. A condensed version of this report entitled: *Microsimulation Models for Social Welfare Programs: An Evaluation* is available at http://www.irp.wisc.edu/publications/focus/pdfs/foc153b.pdf

These three models are, however, partially integrated as depicted by the dotted lines in Exhibit 1. For example, the available supply influences staffing patterns; provider demand influences career decisions of individual providers; and disease prevention and management strategies influence patient health outcomes and the derived demand for services and providers. Efforts are ongoing to increase integration of these three models. The three models run using Statistical Application Software (SAS).

Exhibit 1. Integrated Health Workforce Supply and Demand Model



The health occupations and medical specialties included in this model are summarized in Exhibit 2. Not all occupations are included in the supply analysis, often because of data limitations on entry and exit from low compensated occupations with low barriers to entering the profession.

Exhibit 2. Health Occupations and Specialties Modeled

Occupations & Specialties	Occupations & Specialties, cont.
Physicians & physician assistants	**Advanced practice nurses**
Allergy & immunology	Nurse anesthetists
Anesthesiology	Nurse midwives
Cardiology	Nurse practitioners (by specialty)
Colorectal surgery	**Nursing**
Critical care/pulmonology	Registered nurses
Dermatology	Licensed practical/vocational nurses
Emergency medicine	Nurse assistants/aides (incl. home health)
Endocrinology	**Behavioral health (Incl. psychiatrists and NPs/PAs)**
Gastroenterology	Psychologists
Family medicine	Addiction counselors
General internal medicine	Social workers
General pediatrics	Mental health counselors
General surgery	School counselors
Geriatrics	Marriage and family therapists
Hematology & oncology	**Oral health**
Infectious diseases	Dentists
Obstetrics & gynecology	Orthodontists
Occupational medicine	Dental hygienists
Ophthalmology	**Pharmacy**
Orthopedic surgery	Pharmacists
Otolaryngology	Pharmacy technicians
Neonatal/perinatal	Pharmacy aides
Nephrology	**Respiratory care (therapists & technicians)**
Neurological surgery	**Rehabilitation Services**
Pathology	Occupational therapists & assistants
Physical medicine & rehabilitation	Physical therapists & assistants
Plastic surgery	**Therapeutic Services**
Psychiatry	Chiropractor
Radiation oncology	Podiatrists
Radiology	**Vision Services**
Rheumatology	Opticians
Thoracic surgery	Optometrists
Urology	**Nutritionists**
Vascular surgery	**Select diagnostic laboratory professions**
Other specialties	**Select diagnostic imaging professions**

II. HEALTHCARE DEMAND MICROSIMULATION MODEL

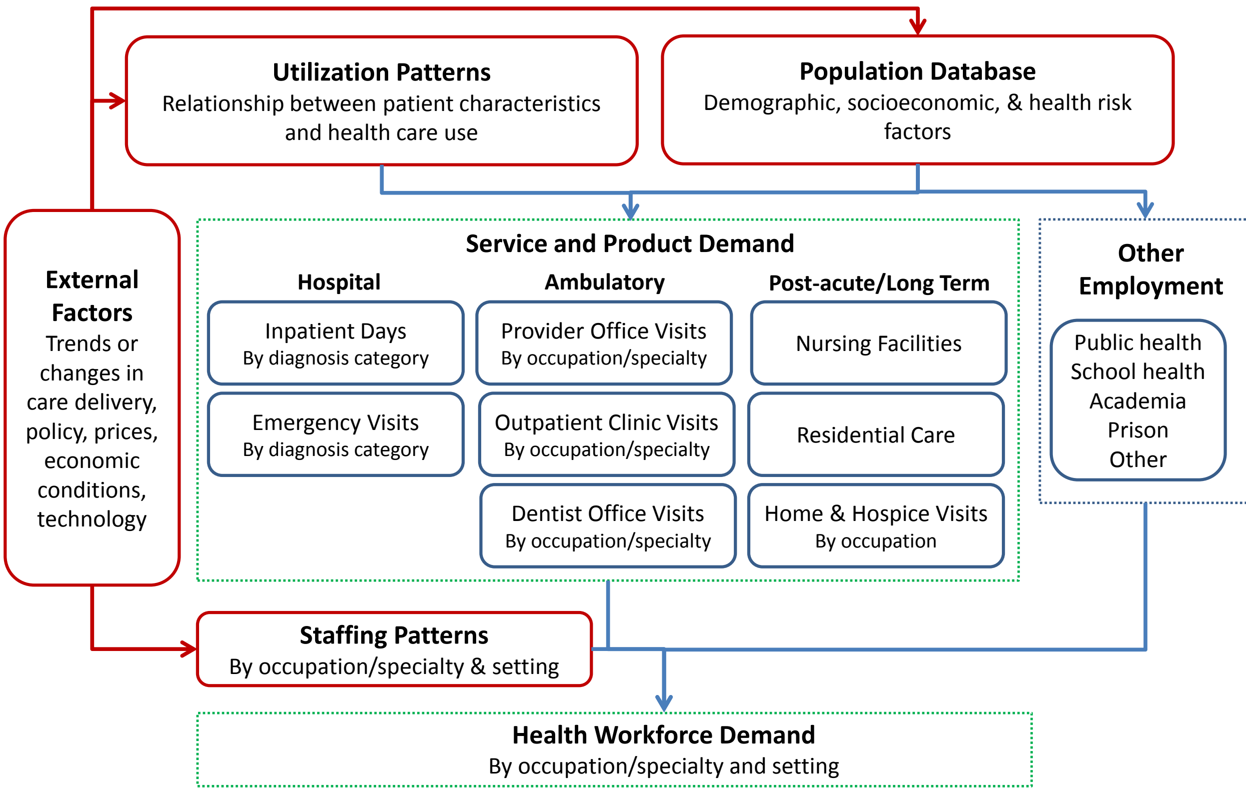
This section provides a brief overview of the HDMM, and then describes creation of the major components: the population file, the health care use equations, and the provider staffing parameters. Data sources and methods for producing national and state demand projections are described, with adaption of the model to individual states described in an appendix. The section ends with a description of the scenarios the HDMM was designed to model.

Overview

The HDMM, as its name implies, models demand for health care services and providers. Demand is defined as the level and mix of health care services (and providers) that are likely to be used based on population characteristics and economic considerations such as price of services and people's ability and willingness to pay for services. The HDMM was designed to also run a limited set of scenarios around "need" for services. Need is defined as the health care services (and providers) required to provide a specified level of care given the prevalence of disease and other health risk factors. Need is defined in the absence of economic considerations or cultural considerations that might preclude someone from using available services.

The HDMM has three major components: (1) a population database with information for each person in a representative sample of the population being modeled, (2) health care use patterns that reflect the relationship between patient characteristics and health care use, and (3) staffing patterns that convert estimates of health care demand to estimates of provider demand (Exhibit 3). Demand for services is modeled by employment setting. Demand is also modeled by (a) diagnosis category for hospital inpatient care and emergency department visits, and (b) health care occupation or medical specialty for office and outpatient visits. The services demand projections are workload measures, and demand for each health profession is tied to one or more of these workload measures. For example, current and future demand for primary care providers is tied to demand for primary care visits, demand for dentists is tied to projected demand for dental visits, etc. External factors—such as trends or changes in care delivery—can influence all three major components of HDMM.

Exhibit 3. Schematic of Healthcare Demand Microsimulation Model



Population Input Files

The population files used in the model contain person-level data for a representative sample of the population of interest. The population of interest might be the entire U.S., an individual state, a county within a state, or some other geographic unit such as a region or ZIP code. When a population file is created for a specified area, demand estimates can be produced for subsets of the population—e.g., subsets defined by insurance type, patient demographic, or other tracked characteristic of the population. Creation of the national and state population files starts with merging three publicly available surveys:

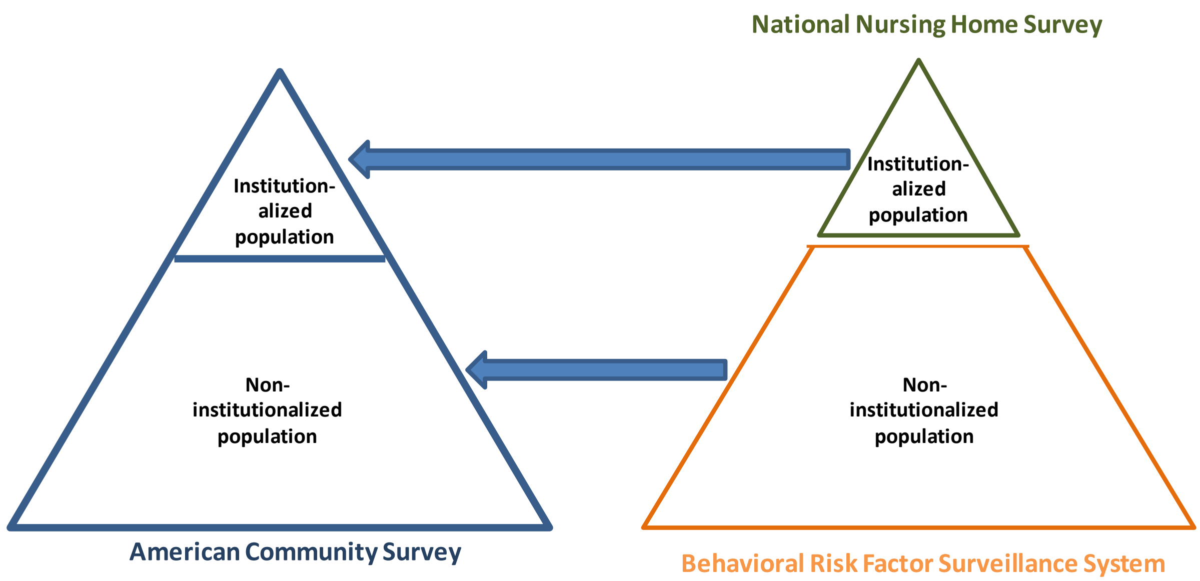
- **American Community Survey (ACS)**. Each year the Census Bureau collects information on approximately three million individuals grouped into approximately one million households. For each person, information collected includes: demographics, household income, medical insurance status, geographic location (e.g., state and sub-state [for multi-year files]), and type of residency (e.g., community-based residence or nursing home). Each year HDMM is updated with the latest available file, and HDMM was updated with the 2014 ACS (n=3,132,610 observations) in November 2015.
- **Behavioral Risk Factor Surveillance System (BRFSS)**. The Centers for Disease Control and Prevention (CDC) annually collects data on a sample of over 500,000 individuals. Similar to the ACS, the BRFSS includes demographics, household income, and medical insurance status for a stratified random sample of households in each state. The BRFSS, however, also collects detailed information on presence of chronic conditions (e.g., diabetes, hypertension) and other health risk factors (e.g., overweight/obese, smoking). One limitation of BRFSS is that as a telephone-based survey it excludes people in institutionalized settings (e.g., nursing homes) who do not have their own telephone. We

combined the two latest BRFSS files (2013 and 2014) to create a joint file with close to one million individuals. HDMM was updated with the BRFSS files in November 2015.

- **National Nursing Home Survey (NNHS)**.The Centers for Disease Control and Prevention collected data on a national sample of 16,505 nursing home residents in 2004 (the latest year for which individual data were collected). In addition to demographics, the NNHS collects information on chronic conditions and health risk factors of this population. Use of data on nursing home residents is important because this institutionalized population has much poorer health and different health care use patterns compared to their peers living in the community. The statistical match process that combines NNHS with the institutionalized population in ACS, as well as model calibration using current estimates of the size of the nursing home population (Exhibit A- 1), helps ensure demographic representativeness of the current nursing home population.

The HWSM population database merges information from these sources using a statistical matching process that combines patient health information from the BRFSS and NNHS with the larger ACS file that has a representative population in each state (and for some sub-state levels). Using information on residence type, we stratified the ACS population into those residing in nursing facilities to be matched to people in the NNHS, and those not residing in nursing facilities to be matched to people in BRFSS (Exhibit 4). For the non-institutionalized population, we randomly matched each individual in the ACS with someone in the BRFSS from the same state, sex, age group (15 groups), race/ethnicity, insured/uninsured status, and household income level (8 levels).[14] Individuals categorized as residing in a nursing home were randomly matched to a person in the NNHS in the same sex, age group, and race-ethnicity strata. Under this approach, some BRFSS or NNHS individuals might be matched multiple times to similar people in the ACS, while some BRFSS or NNHS individuals might not be matched.

Exhibit 4. Population Database Mapping Algorithm



[14] The first round of matching produced a match in the same strata for 94% of the population. To match the remaining 6%, we collapsed the eight income levels into four (1% matched), then dropped the race/ethnicity dimension (1% matched), then repeated the same criteria as the first round except removed State as a strata (remaining 4% matched).

Exhibit 5 summarizes the population characteristics available in each source file and the characteristics used for the statistical match process. This detailed information for each person captures systematic geographic variation in demographics, socioeconomic characteristics, and health risk factors (e.g., obesity, smoking, diabetes and cardiovascular disease prevalence) that reflect regional differences in diet, physical activity, and other health-related behavior.

Exhibit 5. Characteristics Available for Each Person in Representative Population Sample

Population Characteristics	Match Strata		Source		
	ACS-BRFSS	ACS-NNHS	ACS	BRFSS	NNHS
Demographics					
Children age groups: 0-2, 3-5, 6-13, 14-17 Adult age groups: 18-34, 35-44, 45-64, 65-74, 75+	✓[b]	✓[b]	✓	✓	✓
Sex	✓	✓	✓	✓	✓
Race/ethnicity: non-Hispanic white, non-Hispanic black, non-Hispanic other, Hispanic	✓	✓	✓	✓	✓
Health-related lifestyle indicators [a]					
Body weight: normal, overweight, obese				✓	✓
Current smoker status				✓	✓
Socioeconomic conditions and insurance					
Family 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+)	✓		✓	✓	
Has medical insurance	✓	✓	✓	✓	✓
Medical insurance type (private, public, self-pay)				✓	✓
In a managed care plan (extrapolated using regression analysis based on MEPS data)					
Chronic conditions					
Diagnosed with asthma				✓	✓
Diagnosed with arthritis, heart disease, diabetes, hypertension [a]				✓	✓
History of cancer, heart attack, or stroke [a]				✓	✓
Geographic location					
State (or other geographic area such as county)	✓		✓	✓	
Living in a metropolitan area			✓	✓	

Note: [a] Characteristics available only for adults. [b] Fifteen age groups are used for the statistical match process: ages 0-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, and 85+. Then, individual ages are used to create the nine age groups above for modeling demand for health care services. The smaller number of age groups used for modeling demand for health care services reflects smaller sample size in the data sources used for modeling patterns of health care use.

The ACS provides a representative sample of the population in each state for the most current year available, with sample weights that can be aggregated to produce state (or national) totals. Developing demand forecasts for future years requires incorporating state-specific population projections and national population projections developed by the U.S. Census Bureau (see Appendix Exhibit A- 2). For source information on population projections). Using the population projections, we developed new sample weights for each individual so that when these weights are used the population file produces population estimates for each future year through 2025 or beyond consistent with published population projections.

Health Care Use

Projected future use of health care services, based on population characteristics and patterns of health-seeking behavior, produce workload measures used to project future demand for health care providers. HDMM uses prediction equations for health care use based on recent patterns of care use, but also can model scenarios where health care use patterns change in response to emerging care delivery models or other factors.

Demand Determinants and Prediction Equations

Health seeking behavior is generated from econometrically estimated equations using data from ~170,000 participants in the pooled 2009-2013 files of the Medical Expenditure Panel Survey (MEPS). We pooled multiple years of data to provide a sufficient sample size for regression analysis for smaller health professions and diagnosis categories. Over time, as a new year of data becomes available and is added to the analytic file the oldest year in the analysis file is dropped. We used the 2013 Nationwide Inpatient Sample (NIS), with ~8 million discharge records, to model the relationship between patient characteristics and length of hospitalization by primary diagnosis category.

Many of the population characteristics (including demographics and socioeconomic circumstances) are likely correlated with cultural and other factors (e.g., access constraints) that influence use of health care services and are omitted from the regressions due to data limitations. Consequently, the observed relationship between annual use of health care services and observed patient characteristics reflects correlation rather than causality.

Poisson[15] regression was used to model annual office visits, annual outpatient visits, annual home health/hospice visits and inpatient days per hospitalization. These regressions were estimated separately for children versus adults. Separate regressions were estimated by physician specialty or non-physician occupations—e.g. dentists, physical therapists, psychologists—for office-based care. Likewise, separate regressions were estimated for occupations providing home health care. The dependent variable was annual visits (for office, outpatient, and home health) and inpatient days per hospitalization (for hospitalizations). The explanatory variables were the patient characteristics available in both MEPS (or NIS for hospital length of stay) and the constructed population file (Exhibit 6).

Logistic[16] regression was used to model annual probability of hospitalization and annual probability of emergency department visit for approximately two dozen categories of care defined by primary diagnosis code (see Appendix I Exhibit A- 3 for the category definitions). The dependent variable for each regression is whether the patient had a hospitalization (or ED visit) during the year for each of the condition categories.

The model contains several hundred prediction equations for health care use, with examples of the regression output for cardiology care presented in Exhibit 6 and for primary care presented in Exhibit 7. The numbers in

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[15] Poisson regression is often used when the dependent variable (annual visits) is a count variable with a skewed distribution—i.e., many people have 0, 1, or 2, visits, but the number of people with higher volume of visits (3, 4, 5, etc.) declines at the higher volume levels.

[16] Logistic regression is often used when the dependent variable is binary (yes/no). The sample size of MEPS is too small to accurately model patients with multiple hospitalizations and multiple emergency department visits—especially when modeling at the diagnosis category level.

Exhibit 6 reflect either rate ratios (for office and outpatient visits, or inpatient days) or odds ratios (for ED visits and hospitalizations). For all types of cardiology-related care there is a strong correlation with patient age (controlling for other patient characteristics modeled). For example, relative to patients age 75 or older, patients age 65-74 have only 83% as many office visits but have 21% more outpatient visits. Both estimates are statistically different from 1.0 (where a ratio of 1.0 would indicate no statistical difference with the comparison category). Patients age 65-74 have higher odds of a cardiology-related ED visit (i.e., primary diagnosis was cardiology-related), and 50% higher odds of a cardiology-related hospitalization. However, the length of hospitalization averages only 93% as long as the hospitalization for the age 75 or older patient.

Blacks tend to have fewer office and outpatient visits than whites, but higher odds of ED visits or hospitalizations and longer average length of hospital stay. Obesity increases use of cardiology-related services. Smoking is associated with fewer office and outpatient visits to a cardiologist but higher rates of ED visits (likely reflecting correlation rather than causality in the case of ambulatory care, as smoking is a risk factor for heart disease but could be correlated with aversion to visit a doctor). Lower income is associated with less use of ambulatory care and more use of ED visits and hospitalization. Having any medical insurance is associated with much greater use of ambulatory care, and if the insurance is Medicaid then there is even greater use of cardiology services across all care delivery settings. The presence of chronic medical conditions—and especially heart disease, hypertension, and history of heart attack—are associated with much greater use of cardiology services across care delivery settings. Patients in metropolitan areas have more ambulatory visits than patients in non-metropolitan areas. Regression equations for other types of care (whether by medical specialty or condition category) exhibit similar patterns that are consistent with expectations and the health research literature.

Office and outpatient visits by adults to a family medicine (FM) or general internal medicine (GIM) are presented for comparison (Exhibit 7). Many of the patient characteristics correlated with use of primary care services are similar to characteristics associated with greater use of cardiologist services—e.g., the presence of chronic conditions like cardiovascular disease and diabetes. Interestingly, being overweight or obese and being a smoker are associated with more visits to FM and fewer to GIM. Rising family income and residing in a metropolitan is associated with greater use of GIM services but lower use of FM services.

For care provided in the emergency department we link demand for emergency physicians to total demand for emergency visits (so 10% growth in visits would translate to 10% growth in demand for emergency physicians under the status quo scenario). Specialist physicians sometimes provide consults for emergency visits, and the mix of patients and their diagnoses are expected to change over time. Using the 2010 and 2011 NHAMCS[17] we estimated a logistic regression where the dependent variable was whether during the visit a second physician was seen. As summarized in Exhibit 8, the explanatory variables include specialty category (defined by primary diagnosis), patient demographics (age, sex, and race), insurance status and whether insured through Medicaid, and whether the patient lives in a metropolitan or non-metropolitan location. As illustrated by the odds ratios, the likelihood that a specialist physician will be consulted during the visit differs by condition category, but in general a second physician is most likely to be consulted if the patient's primary diagnosis is related to neurological surgery, vascular surgery, or cardiology. Patients with a primary diagnosis related to dermatology, otolaryngology, or rheumatology are much less likely to see a second physician during their ED visit. Consults are more likely for older patients, males, insured, not on Medicaid, and living in a metropolitan area.

[17] The 2011 NHAMCS files is the latest file available (released June 2015).

Exhibit 6. Sample Regressions: Adult Use of Cardiology Services

Parameter [a]	Office Visits [b]	Outpatient Visits [b]	Emergency Visits [c]	Hospitalizations [c]	Inpatient Days [d]
Age					
18-34 years	0.11**	0.24**	0.66**	0.40**	0.84**
35-44 years	0.22**	0.63**	0.95	0.76**	0.80**
45-64 years	0.50**	0.86**	1.05	1.10	0.86**
65-74 years	0.83**	1.21**	1.11	1.50**	0.93**
75+ years	1.00	1.00	1.00	1.00	1.00
Male	1.13**	1.59**	0.89*	1.11	0.97**
Race- Ethnicity					
Non-Hispanic White	1.00	1.00	1.00	1.00	1.00
Non-Hispanic Black	0.79**	0.97	1.36**	1.32**	1.14**
Non-Hispanic Other	0.90**	0.75**	0.86	0.94	1.10**
Hispanic	0.79**	0.68**	0.93	0.84**	1.07**
Body Weight					
Normal	1.00	1.00	1.00	1.00	
Overweight	1.04**	1.09**	0.87**	0.82**	
Obese	1.11**	1.18**	1.01	1.02	
Current Smoker	0.73**	0.84**	1.22**	1.11	
Household Income					
<$10,000	0.90**	0.97	1.23**	1.19**	
$10,000 to <$15,000	0.92**	0.91**	1.16*	1.20**	
$15,000 to < $20,000	0.93**	0.93*	0.82	0.99	
$20,000 to < $25,000	0.89**	0.73**	1.15	1.06	
$25,000 to < $35,000	0.92**	0.96	1.16*	1.05	
$35,000 to < $50,000	0.88**	1.07*	0.91	0.93	
$50,000 to < $75,000	0.96*	1.17**	0.93	0.82**	
$75,000 or higher	1.00	1.00	1.00	1.00	
Insurance					
Has insurance	2.61**	2.09**	0.92	1.09	0.99*
In Medicaid	1.36**	1.30**	1.59**	1.71**	1.23**
In managed care plan	1.00	1.24**	0.99	0.99	
Diagnosed with					
Arthritis	1.10**	1.24**	0.96	0.96	
Asthma	1.04*	1.08**	1.00	1.07	
Diabetes	1.15**	1.34**	1.01	1.19**	1.02**
Heart disease	8.50**	10.73**	2.93**	3.84**	
Hypertension	1.55**	1.13**	3.86**	2.66**	
History of cancer	1.06**	1.11**	1.01	0.99	
History of heart attack	1.63**	1.36**	2.36**	2.60**	
History of stroke	1.08**	1.26**	2.92**	3.04**	
Metro Area	1.31**	1.09**	1.07	0.91	1.03**

Notes: Statistically different from 1.00 at the 0.05 (*) or 0.01 (**) level. [a] For children the age categories are 0-2, 3-5, 6-13, and 14-17). The adult regressions include everyone age 18 and older. Variables not available for use in the regression equations for children are body weight, smoking status, and diagnosed with the chronic conditions listed (except for asthma which is included). [b] Rate ratios based on Poisson regression of MEPS data. Dependent variable is annual visits to cardiologist. [c] Odds ratios based on logistic regression of MEPS data. Dependent variable is whether a patient had an emergency visit or hospitalization with a cardiology-related primary diagnosis code. [d] Rate ratios based on Poisson regression of NIS data. Dependent variable is length of stay conditional on hospitalization for cardiology-related primary diagnosis.

Exhibit 7. Sample Regressions: Adult Primary Care Visits

Parameter	Internal Medicine		Family Medicine	
	Office Visits	Outpatient Visits	Office Visits	Outpatient Visits
Age				
18-34 years	0.19**	0.30**	0.54**	0.86**
35-44 years	0.40**	0.42**	0.73**	0.94
45-64 years	0.59**	1.05	0.84**	1.07
65-74 years	0.81**	1.79**	0.90**	1.29**
75+ years	1.00	1.00	1.00	1.00
Male	0.82**	1.01	0.82**	0.98
Race- Ethnicity				
Non-Hispanic White	1.00	1.00	1.00	1.00
Non-Hispanic Black	0.87**	2.09**	0.77**	1.21**
Non-Hispanic Other	1.31**	1.58**	0.86**	1.21**
Hispanic	0.59**	1.30**	0.99	1.54**
Body Weight				
Normal	1.00	1.00	1.00	1.00
Overweight	0.97*	0.79**	1.05**	1.05*
Obese	0.99	0.83**	1.15**	1.11**
Current Smoker	0.90**	0.92**	1.05**	1.19**
Household Income				
<$10,000	0.80**	1.62**	1.16**	1.22**
$10,000 to <$15,000	0.79**	1.12**	1.18**	1.40**
$15,000 to < $20,000	0.81**	1.33**	1.14**	1.21**
$20,000 to < $25,000	0.77**	0.95	1.08**	1.22**
$25,000 to < $35,000	0.77**	1.04	1.08**	1.42**
$35,000 to < $50,000	0.84**	1.05	1.08**	1.48**
$50,000 to < $75,000	0.83**	1.17**	1.06**	1.13**
$75,000 or higher	1.00	1.00	1.00	1.00
Insurance				
Has insurance	2.36**	0.99	1.65**	1.19**
In Medicaid	1.19**	2.29**	1.26**	1.64**
In managed care plan	1.07**	1.42**	1.07**	1.34**
Diagnosed with				
Arthritis	1.61**	1.64**	1.49**	1.59**
Asthma	1.38**	1.54**	1.3**	1.26**
Diabetes	1.39**	1.06**	1.33**	1.08**
Heart disease	1.26**	1.60**	1.15**	1.18**
Hypertension	1.57**	1.53**	1.52**	1.62**
History of cancer	1.28**	1.48**	1.08**	1.20**
History of heart attack	0.88**	0.86**	0.98	1.21**
History of stroke	1.16**	0.93*	1.11**	1.82**
Metro Area	1.62**	1.47**	0.93**	1.15**

Notes: Statistically different from 1.00 at the 0.05 (*) or 0.01 (**) level. Rate ratios based on Poisson regression of MEPS data. Dependent variables are annual office or outpatient visits to a general internist or family physician.

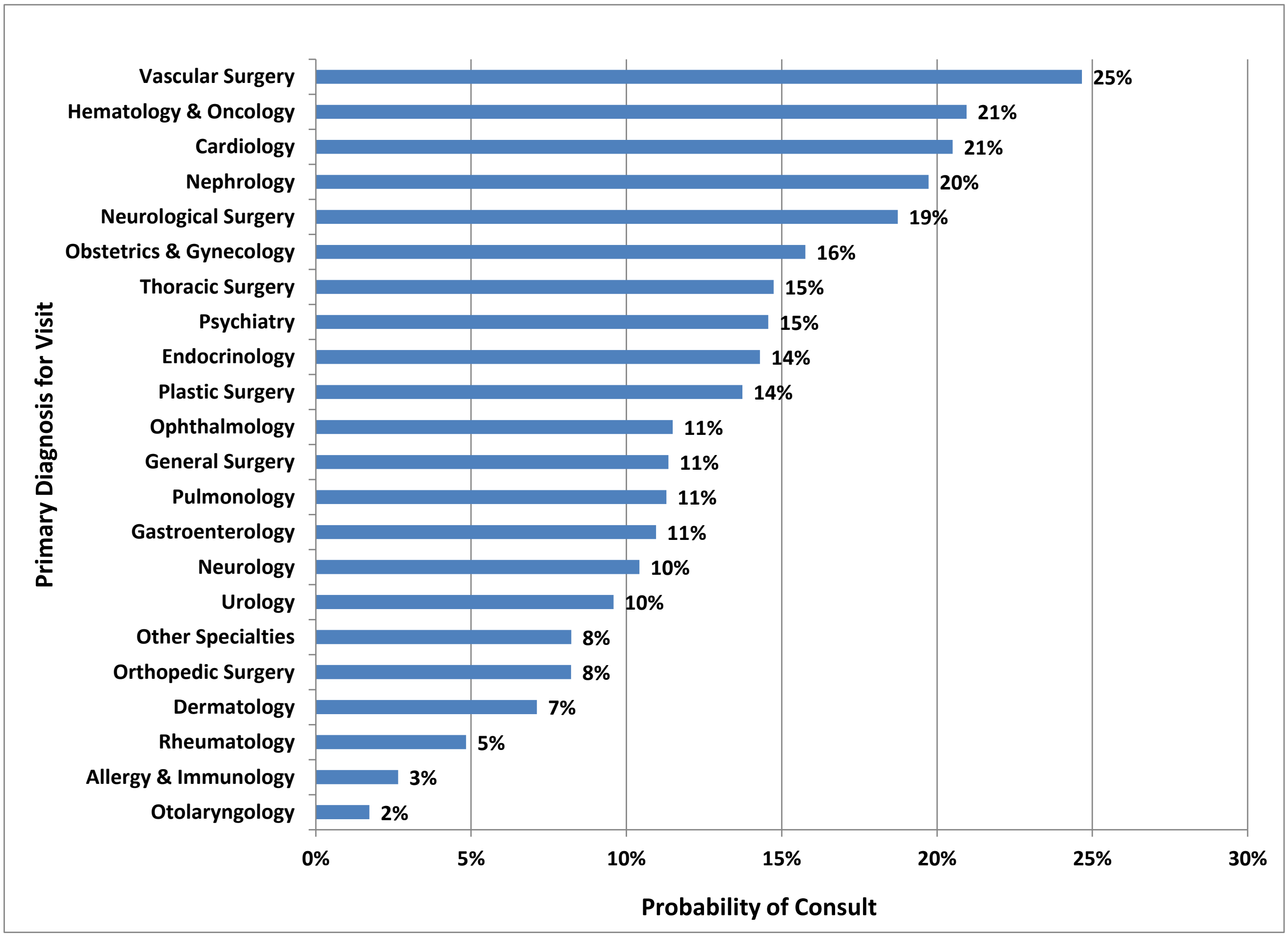
For illustration, applying the logistic regression results to a female patient age 65-74, non-Hispanic white, and living in a metropolitan area produces the following probabilities of having a consult tied to the primary diagnosis for the emergency visit (Exhibit 9). The probabilities range from a high of 25% if the primary diagnosis is in the category of vascular surgery, to a low of 2% is the primary diagnosis is in the category of otolaryngology.

Exhibit 8. Logistic Regression for Emergency Department Consultation

Parameter	Odds Ratio	95% Confidence Interval	
Diagnosis category (General Surgery comparison group) [a]			
Cardiology	2.65	2.21	3.17
Dermatology	0.79	0.63	0.98
Endocrinology	1.71	1.36	2.16
Gastroenterology	1.26	1.06	1.50
Hematology	2.72	2.11	3.50
Infectious Disease	0.77	0.58	1.03
Nephrology	2.52	1.54	4.13
Neurological Surgery	2.36	1.62	3.44
Neurology	1.19	0.97	1.46
Obstetrics & Gynecology	1.92	1.53	2.41
Ophthalmology	1.33	0.95	1.87
Orthopedic Surgery	0.92	0.78	1.08
Otolaryngology	0.18	0.10	0.34
Plastic Surgery	1.63	1.01	2.64
Psychiatry	1.75	1.46	2.10
Pulmonology	1.31	1.12	1.52
Rheumatology	0.52	0.36	0.76
Thoracic Surgery	1.77	1.50	2.09
Urology	1.09	0.92	1.29
Vascular Surgery	3.36	1.61	7.00
Female	0.81	0.76	0.86
Age (45-65 comparison group)			
0-2	0.40	0.33	0.48
3-5	0.37	0.28	0.47
6-12	0.51	0.43	0.61
13-17	0.60	0.51	0.72
18-34	0.58	0.53	0.64
35-44	0.72	0.64	0.80
65-74	1.48	1.32	1.66
75+	1.50	1.36	1.67
Race (non-Hispanic white comparison group)			
Hispanic	0.88	0.79	0.99
Non-Hispanic black	1.06	0.97	1.15
Non-Hispanic other	1.29	1.12	1.49
Insured	1.46	1.30	1.64
On Medicaid	0.88	0.80	0.96
Lives in metropolitan area	1.75	1.56	1.95
2011 (vs 2010)	1.06	0.99	1.13

Source: Logistic regression analysis of the 2010 and 2011 NHAMCS. [a] Diagnosis categories defined by ICD-8 diagnosis and procedure codes to reflect types of care most likely provided by a physician specialty.

Exhibit 9. Illustration of Probability of Emergency Department Consultation



Note: Calculated probabilities are for a female patient age 65-74 who is non-Hispanic white and living in a metropolitan area.

Demand for medications is the workload driver to model demand for pharmacy-related health occupations. The NAMCS and NHAMCS indicate Rx prescriptions prescribed by a health provider, though this is used as a proxy for number of prescriptions filled (under the assumption that the ratio of prescribed-to-filled remains relatively constant over time).[18] Patients who visit a nephrologist in an office setting average 4.85 Rx prescriptions per visit, for example, while for primary care visits the average is 1.67 Rx prescriptions per visit (Exhibit 10). To model projected growth in demand for pharmacy-related occupations, under the status quo scenario, provider demand is tied to projected growth in number of Rx prescriptions.

[18] Analyses based on the 2010 NAMCS and NHAMCS are being updated to the 2012 NAMCS and 2011 NHAMCS. The MEPS is also being analyzed as a possible source of data for modeling demand for prescriptions.

Exhibit 10. Average Rx Prescriptions per Health Care Visit

Physician Specialty	Office	Outpatient	Emergency
Nephrology	4.85	4.59	2.16
Cardiology	4.11	4.21	2.34
Vascular Surgery	3.52	3.41	1.61
Endocrinology	3.51	3.94	2.05
Thoracic Surgery	3.40	3.09	1.69
Pulmonology	2.81	2.90	2.37
Neurology	2.69	2.82	2.31
Gastroenterology	2.48	2.86	2.20
Hematology & Oncology	2.47	3.41	2.09
Psychiatry	2.41	2.10	1.37
Rheumatology	2.30	2.76	1.70
Urology	2.24	2.35	2.51
Orthopedic Surgery	2.10	2.53	1.89
Allergy & Immunology	2.09	2.55	2.02
Dermatology	2.06	2.59	2.08
Plastic Surgery	2.00	1.69	2.21
Ophthalmology	1.84	2.19	1.53
Otolaryngology	1.78	2.17	2.07
Primary Care	1.67	1.70	0.60
General Surgery	1.57	1.81	1.53
OBGYN	1.46	1.83	1.67
Colorectal Surgery	1.36	1.81	1.95
Neurological Surgery	1.32	1.51	1.55
Neonatal-perinatal	0.36	1.07	0.52
Other Med Spec	1.62	1.79	1.37

Note: Average prescriptions per visit based on analysis of 2010 NAMCS and NHAMCS files.

To model demand for oral health services we analyzed the MEPS Dental Visits File with for the period 2009-2013. These combined files contain ~64,000 dental visits where the service was not for cleaning, 106,000 visits for dental cleaning, and over 2,000 visits for orthodontic services. We estimated six Poisson regressions—for children and for adults, by three types of services: 1) dental, 2) dental cleaning, and 3) orthodontic. These regressions quantify the relationship between patient characteristics and annual oral health visits similar to the regression output summarized in Exhibit 6. The regression results show that use of oral health services is highly correlated with insurance status (with medical insurance used as a proxy for dental insurance), household income, living in a metropolitan area, patient age, and race/ethnicity.

Health Care Use Calibration

MEPS is a representative sample of the non-institutionalized population, and although the health care use prediction equations are applied to a representative sample of the entire U.S. population parts of the model require calibration to ensure that at the national level the predicted health care use equals actual use. Applying the prediction equations to the population for 2011 through 2013 creates predicted values of health care use in those years (e.g., total hospitalizations, inpatient days, and ED visits by specialty category, and total office visits by physician specialty). For model calibration, we compared predicted national totals to estimates of national total hospitalizations and inpatient days, by diagnosis category, derived from the 2013 NIS. National ED visits and office visits came from the 2011 NHAMCS and 2012 NAMCS, respectively.

Multiplicative scalars were then created by dividing national estimates by predicted estimates. For example, if the model under-predicted ED visits for a particular diagnosis category by 10% then a scalar of 1.1 was added to the prediction equation for that diagnosis category.

Applying this approach to diagnosis/specialty categories, the model's predicted health care use was consistent with national totals for most settings (see Exhibit 11 for calibration scalars for physician office visits). Setting/category combinations where the model predicted less accurately (and therefore required larger scalars) tended to cluster around diagnosis categories in the ED characterized by lower frequency of visits likely due to a combination of small sample size in both MEPS and NHANES.

Exhibit 11. HDMM Calibration: Physician Office Visits

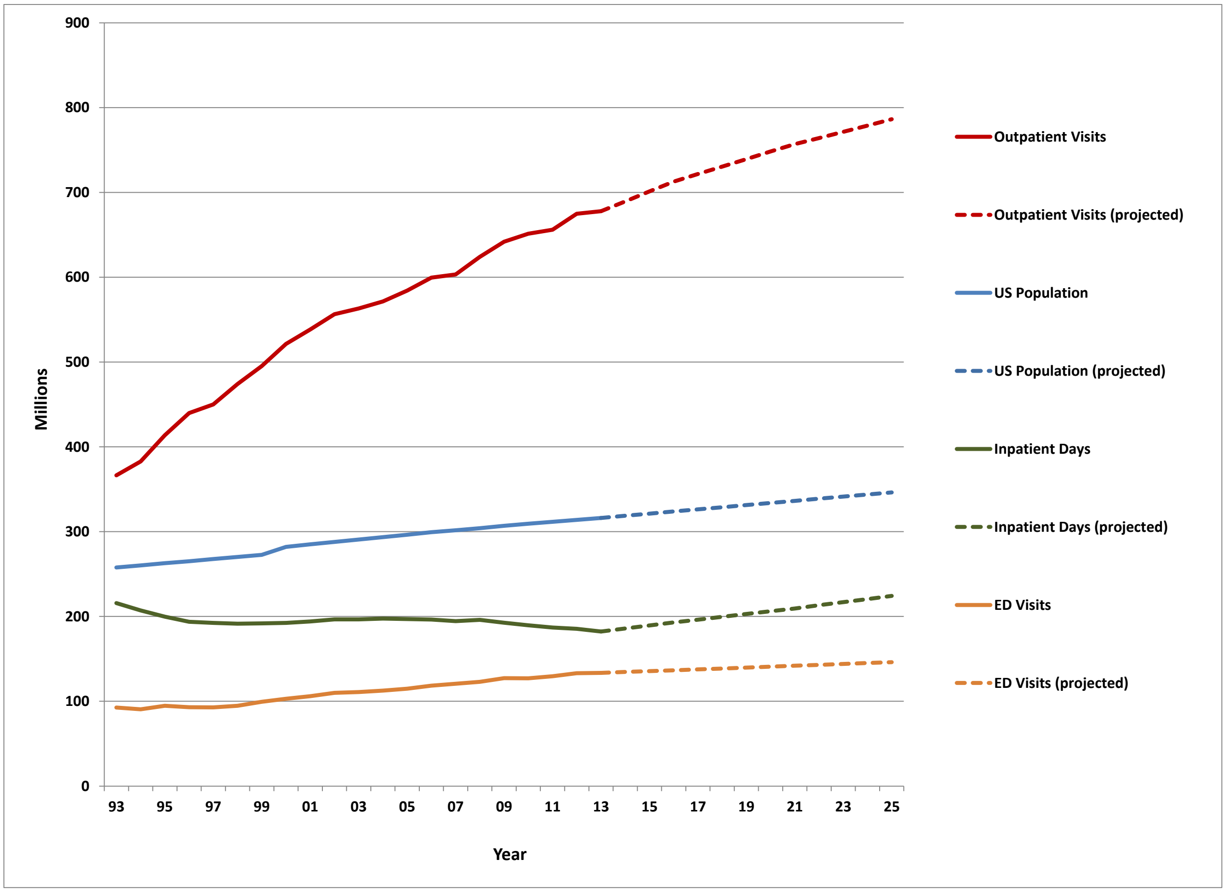
Specialty	NAMCS Visits (in thousands), 2012 [a]	HDMM Initial Visits Pre-Scalar (in thousands), 2012	Scalar
Family Medicine	192,342	260,979	0.737
Pediatrics	129,583	77,222	1.678
Internal Medicine	117,998	53,019	2.226
Obstetrics & Gynecology	71,657	57,282	1.251
Orthopedic Surgery	47,484	47,148	1.007
Ophthalmology	43,934	56,906	0.772
Dermatology	38,702	32,947	1.175
Psychiatry	29,209	46,420	0.629
Cardiovascular Diseases	23,856	19,857	1.201
Otolaryngology	19,133	14,317	1.336
Urology	18,055	14,099	1.281
General Surgery	15,176	9,883	1.536
Neurology	14,242	15,477	0.920
Oncology	13,003	24,507	0.531
Pulmonology	9,719	7,496	1.297
Allergy	8,094	15,046	0.538
All other specialties	136,443	4,438	30.741

[a] http://www.cdc.gov/nchs/data/ahcd/namcs_summary/2012_namcs_web_tables.pdf

National Trends in Health Care Use

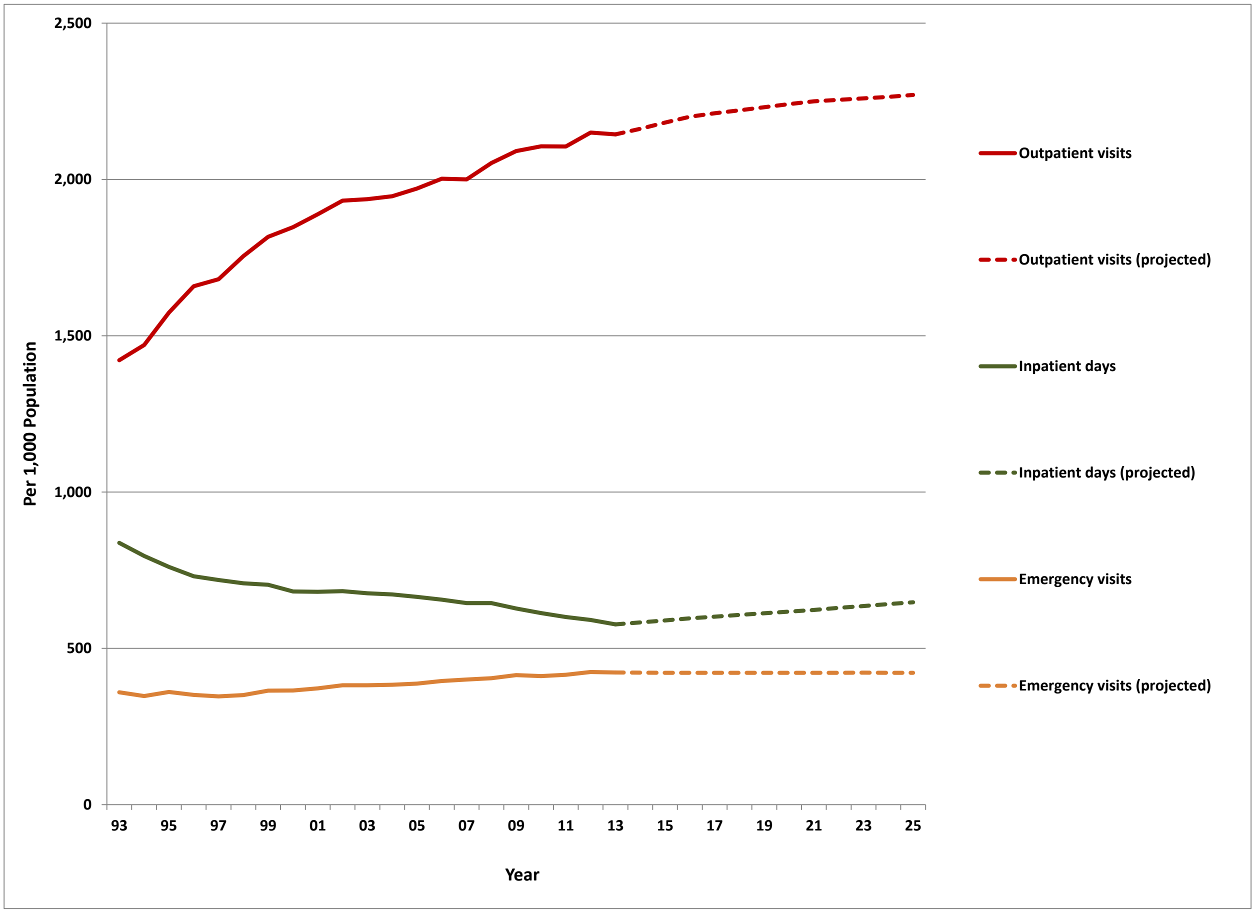
At an aggregate level, as shown in Exhibit 12, between 1993 and 2013 the annual number of hospital outpatient visits in the U.S. climbed steadily; the number of ED visits rose (though at a slower pace than growth in outpatient visits); and the number of hospital inpatient days declined slightly. Declines in inpatient days occurred during the mid-to-late 1990s (possibly influenced by the growing influence of health maintenance organizations), and again during the 2008-2013 period (possibly influenced by the economic recession). During this entire period the lack of growth in hospital inpatient days also reflects changes in technology and medical practice patterns that allowed some care to be provided on an outpatient basis where previously the care required hospitalization, changes in reimbursement policies, and overall improvements in standards of care to reduce risk of nosocomial complications and speed patient recovery time. Applying health care use patterns observed during 2009-2013 to the projected future population and accounting for the likely impact of expanded medical coverage under the Affordable Care Act (if expanded coverage occurs as reflected in Congressional Budget Office projections), then between 2013 and 2025 the HDMM projects a continuation of current growth trends (as reflected by the dotted lines). HDMM projects demand will rise slowly for inpatient days—reflecting large growth in the size of the elderly population with their high use of hospital care. By 2025, the projected national level of inpatient days will be similar to the level observed in 1993.

Exhibit 12. National Trends in Hospital Care: 1993-2013, Projected to 2025



At the national level, outpatient visits per 1000 population also are projected to continue growing though at a slightly lower growth rate than historical patterns (Exhibit 13). Emergency visits per 1000 population are projected to remain relatively constant. There is a projected slight uptick in inpatient days per 1000 population (reflecting the rapidly growing elderly population).

Exhibit 13. National Trends in Hospital Care per 1000 Population: 1993-2013, Projected to 2025



Health Workforce Staffing Patterns

Demand for health care workers is derived from the demand for health care services. The status quo scenario in HDMM extrapolates current staffing levels as reflected by national ratios of health care use to providers. For example, demand for RNs under the status quo is modeled based on the current national ratio of inpatient days-to-RNs to model RNs in hospital inpatient settings, the national ratio of ED visits-to-RNs to model demand for RNs in emergency departments, the national ratio of office visits-to-RNs to model demand for RNs in office settings, etc.

The number of RNs (and number of providers in many of the health occupations modeled) comes from analysis of the 2014 Occupational Employment Statistics (OES) survey data collected from employers by the Bureau of Labor Statistics. OES data collects and reports employment data by detailed health occupation, industry sector, and state. Limitations of OES data are that it counts job positions (which can over count the workforce in occupations that have a high proportion of part time workers), and the OES data are for employed individuals (which can under count the workforce in occupations with a high proportion of self-employed individuals such as dentists or physicians). Hence, for some professions alternative data sources are used to estimate staffing patterns (as documented in the table notes for Exhibit A- 4 through Exhibit A- 9 in Appendix I).

For many occupations demand is tied to one workload measure—e.g., demand for dentists is tied to demand for dental visits (excluding dental cleaning visits), and demand for dental hygienists is tied to demand for dental cleanings. For nurses, physicians, APRNs, PAs, and health occupations that work in multiple care delivery settings there are multiple workload measures specific to each occupation and employment setting. The use of multiple workload measures reflects that demand in each setting will grow at different rates. The workload measures and national staffing ratios are summarized in Appendix I (Exhibit A- 4 through Exhibit A-9).

In addition to using current staffing ratios to model a status quo scenario, HDMM was designed to model possible changes in staffing patterns to reflect emerging care delivery models as informed by the literature. These scenarios are discussed in more detail later and are also areas of ongoing research. Population health risk factors affect the demand for health care services, but the HDMM staffing currently does not account for variation across geographic areas or over time in average patient acuity level for those who seek care. This is also an area of ongoing research.

Scenarios

The capabilities of HDMM to model alternative demand scenarios continue to evolve, and scenarios previously modeled continue to be refined as new information becomes available. Many of these scenarios have been described and the demand implications summarized in previous publications.[19]

Status Quo

This scenario models the implications of changing demographics as the population grows, ages, and becomes more racially and ethnically diverse. Under this scenario health care use and delivery patterns are assumed to remain consistent with current patterns (i.e., observed during the 2009-2013 period as reflected in the MEPs and the 2013 NIS). Prevalence of disease and other health risk factors (e.g., smoking and obesity) remain constant controlling for demographics, but do change at the aggregate level associated with changing demographics. For example, prevalence of diabetes and heart disease will rise as the population ages but do not change independent of changing demographics.

Expansion of Medical Insurance Coverage under the Affordable Care Act

This scenario builds on the Status Quo scenario, but also models the anticipated impact of expanded medical insurance coverage under the Affordable Care Act. The Congressional Budget Office (CBO) has periodically revised its projections of the number of uninsured who would gain coverage under ACA. Insurance coverage in 2014 is reflected in the 2014 ACS data. CBO projections that in 2015 ACA will decrease the uninsured by 19 million relative to the absence of ACA and a 26 million decline in 2017 and beyond relative to the number of uninsured in the absence of ACA.[20]

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[19] *The Complexities of Physician Supply and Demand: Projections from 2013 to 2025.* Prepared for the Association of American Medical Colleges. Washington, DC: Association of American Medical Colleges; 2015. https://www.aamc.org/download/426242/data/ihsreportdownload.pdf

Dall TM, Gallo PD, Chakrabarti R, West T, Semilla AP, Storm, MV. An Aging Population and Growing Disease Burden Will Require a Large and Specialized Health Care Workforce by 2025. *Health Affairs*. 2013; 32:2013-2020.

[20] Congressional Budget Office. Insurance Coverage Provisions of the Affordable Care Act—CBO's April 2014 Baseline; Table 2. https://www.cbo.gov/sites/default/files/cbofiles/attachments/43900-2014-04-ACAtables2.pdf

For this scenario we first needed to simulate who was likely to gain coverage based on a person's citizenship status (as a proxy for citizen or legal immigrant, and as reflected in the ACS data), household income, health status, and demographics (reflecting that young, healthy individuals are less likely to seek coverage relative to individuals who are less healthy and will likely have greater medical needs).

We assume that a person who gains insurance will have health care use patterns similar to his or her commercially insured counterpart with the same demographics and risk factors. In the HDMM this is essentially done by switching the insurance status of a person from uninsured to insured and holding all other patient characteristics constant.

Previously published modeling results utilizing HDMM indicate that the effects of expanded medical insurance coverage under ACA by 2025 will vary by medical specialty and care delivery setting. For example, increased visits to doctor offices include 5.2% projected growth for otolaryngology, a 5.0% increase for both urology and dermatology, and a 4.7% increase for gastroenterology, with other specialties experiencing smaller increases.[21] For comparison, adult primary care specialties were projected to experience a 2.0% increase in demand for office visits. With many provisions of ACA already implemented, the yet to be realized impact of ACA is diminishing over time.

The scenarios described below build on this scenario that reflects both changing demographics and expanded medical insurance coverage under ACA.

Integrated Care Delivery Model Scenario

A variety of integrated care delivery models are being implemented for both publicly and privately insured populations. These models range in scope from broad-based health system transformation approaches to more targeted interventions. Under the integrated care approach, consumers typically are enrolled in a coordinated care program offered by a private entity using a risk-based payment arrangement. These include medical models such as:

- "**Medical homes**," which use a patient-centered team approach emphasizing prevention, health information technology, care coordination and shared decision making among patients and their providers.
- **Accountable Care Organizations (ACOs) which** create incentives for providers to collaborate in providing and coordinating patient care across settings. ACOs have a strong medical home component.

Integrated care delivery goals include improving the coordination and quality of patient care, reducing inefficiencies, shifting care to lower cost settings and providers as appropriate, improving preventive care efforts, and better controlling medical expenditures.

ACA actively promotes greater use of ACOs, with an estimated 25-31 million Americans currently part of an ACO; a number projected to continue growing.[22] Since ACOs are a relatively new care delivery model, data on their impact on patient use of services, how care is delivered, and the demand implications for the health professions is currently is short supply. The financial results of ACOs in their first years of operation have been mixed, with few experiencing a substantial level of savings that would suggest major shifts in how care

[21] Dall TM, Gallo PD, Chakrabarti R, West T, Semilla AP, Storm, MV. An Aging Population and Growing Disease Burden Will Require A Large and Specialized Health Care Workforce By 2025. *Health Affairs*, 2013; 32:2013-2020.

[22] http://www.accountablecarefacts.org/

is used or delivered. Recent work by Song et al. suggests that ACO participation has had some effect on controlling medical spending growth. During a four year period, medical spending under a global payment model grew 6.8% less as compared with a non-ACO control group.[23] Approximately 40% of this difference was associated with reduced volume of health care services and 60% was due to lower prices.

Many of the goals of ACOs are similar to those of other risk-bearing organizations such as Health Maintenance Organizations (HMOs). Risk-bearing entities such as ACOs and HMOs incorporate financial incentives for patients and physicians to better manage utilization. Looking historically at the effect of these delivery models on use of services provides insights on what might happen if ACOs gain greater prominence.

This care scenario models the demand implications if the entire national population were enrolled in risk-based entities as a proxy for the possible implications of increased ACO enrollment. Predication equations in the HDMM include enrollment in a managed care plan as a predictor of patient use of services.

Expanded Use of Retail Clinics Scenario

The number of retail clinics in operation increased from ~300 to 1,800 between 2007 and 2014.[24] Such clinics typically employ NPs and PAs, and now handle ~10.5 million visits annually.[25] Reasons for seeking care at retail clinics include convenient hours, scheduling and location; and lower cost and no usual source of care (especially for the uninsured).

This scenario models the workforce implications if care currently delivered at primary care physician offices were instead shifted to retail clinics. The scenario first estimates the volume of office visits for the following ten conditions commonly treated at retail clinics:[26]

1. upper respiratory infection (ICD-9 codes 460, 465)
2. sinusitis (461, 473)
3. bronchitis (490, 466)
4. otitis media (middle ear infection) (381, 382) and otitis externa (external ear infection) (380)
5. pharyngitis (462, 463, 034)
6. conjunctivitis (372)
7. urinary tract infection (599, 595)
8. immunization (V03–V06)
9. screening blood pressure check or lab test (V73–V82)
10. other preventive visit (V01, V70, V72, V29–V39)

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[23] Song Z, Rose S, Safran DG, Landon BE, Day MP, Chernew ME. Changes in health care spending and quality 4 years into global payment. *N Engl J Med*, 2014; 371:1704-14.

[24] Mehrotra A, Lave JR. Visits to Retail Clinics Grew Fourfold from 2007 to 2009, Although Their Share of Overall Outpatient Visits Remains Low. *Health Affairs*. September 2012. Vol 32. No. 9, pp.2123-2129. http://content.healthaffairs.org/content/31/9/2123.full.pdf+html

Merchant Medicine's industry Newsletter. November 1, 2014

http://www.merchantmedicine.com/CMSModules/Newsletters/CMSPages/GetNewsletterIssue.aspx

[25] Bachrach et al. *Building a Culture of Health: The Value Proposition of Retail Clinics*. April 2015. http://www.rwjf.org/content/dam/farm/reports/issue_briefs/2015/rwjf419415

[26] Mehrotra A, Margaret C. Wang, Lave JR, Adams JL, and McGlynn, EA. Retail Clinics, Primary Care Physicians, and Emergency Departments: A Comparison Of Patients' Visits. *Health Affairs*, 27, no.5 (2008):1272-1282.

Furthermore, the following assumptions are made when modeling this scenario:

- Patients whose care for the above diagnosis codes is shifted from a primary care physician office to a retail clinic for the above 10 reasons do not have cardiovascular, diabetes, asthma, hypertension or history of stroke. This conservative assumption reflects that patients with these chronic conditions might best be seen by their regular primary care provider to ensure continuity of care.
- Care in retail clinics will primarily be provided by nurse practitioners and physician assistants.
- For care provided in primary care physician offices, it is assumed that 77% of visits to a pediatrician office are handled primarily by a physician (reflecting that between nurse practitioners and physicians 77% of the pediatric workforce is a physician), and that 70% of adult primary care office visits will be handled primarily by a physician.
- Since the 10 categories of visits modeled tend to be less complex than the average office visit, it is assumed that physicians spend less than the average time per visit to handle these cases. To translate the reduction in office visits to demand for physicians, we used the Management Group Medical Association's estimates for the 75^{th} percentile of annual ambulatory patient encounters.
- Approximately 90% of primary care physician encounters with patients are office visits.

Together, these assumptions suggest that 7,970 visits by children to a retail clinic rather than a pediatrician office reduces demand for pediatricians by 1 FTE. Similarly, each 7,855 retail clinic visits by an adult reduces demand for an adult primary care physician by 1 FTE.

Input Summary

The HDMM uses data from a variety of public data sources, which are summarized in Exhibit 14. The model undergoes a major update in November of each year—reflecting that many of the government sponsored annual surveys and data sources used in the model are often released to the public July – October each year.

Exhibit 14. Input Data Summary

Data Source	Use	Latest Available Data	Last Updated
Population File			
American Community Survey, 2014	Create state and national population files	2014	November 2015
Behavioral Risk Factor Surveillance System, 2013-2014	Create state and national population files	2014	November 2015
National Nursing Home Survey, 2004	Create state and national population files	2004	November 2012
CMS Online Survey Certification and Reporting, 2014	Model calibration for total nursing home residents	2014	November 2015
U.S. Census Population Projections	National population projections	2014	November 2014
State Population Projections	Individual state population projections	Various	November 2015
Health Care Use			
Medical Expenditure Panel Survey, 2009-2013	Estimate health seeking behavior	2013	November 2015
Nationwide Inpatient Sample, 2013	Estimate hospital length of stay; model calibration for annual hospital visits	2013	November 2015
National Ambulatory Medical Care Survey, 2012	Model use of non-physician services during office visits; model calibration for annual office visits	2012	November 2015
National Hospital Ambulatory Medical Care Survey, 2011	Model use of non-physician services and physician consults during ED visits; model calibration for annual ED visits	2011	November 2015
Health Care Provider Staffing			
Bureau of Labor Statistics, Occupational Employment Statistics	Estimate provider staffing ratios by health occupation (excluding physicians)	2014	November 2015
American Medical Association, 2014	Estimate physician staffing ratios by specialty	2014	November 2015

III. HEALTH WORKFORCE SUPPLY MODEL

The HWSM is designed to project future supply of health professionals under alternative forecasting scenarios using a microsimulation approach. Supply projections take into consideration characteristics of the current and projected workforce, economic factors, and other external factors (e.g., demand for services) to model likely career choices of health professionals. We describe the logic, data, methods, and assumptions for modeling health workforce supply. We describe the major components of the model and summarize scenarios that can be modeled.

Starting Supply Input Files

The microsimulation model projects future supply by simulating likely workforce decisions of individual, de-identified health care providers. This approach requires developing a starting supply file of **all providers** (preferred approach) or a **representative sample** of providers (e.g., from survey data). When modeling supply for individual states and at the sub-state level the primary data source of de-identified, individual-level provider data is state licensure files.[27] These files typically contain occupation/specialty, active/inactive status, geographic area where working, and demographics. Age is the most important demographic information used to model workforce decisions as hours worked patterns and retirement probabilities are highly correlated with age. Workforce decisions (e.g., hours worked patterns) also vary systematically by sex. Race/ethnicity is a new component being added to the supply model for some occupations (currently RNs and LPNs). In addition to data on activity status and demographics of the workforce, licensure files sometimes contain information collected via survey at time of re-registration such as weekly patient care hours worked, employment setting, and retirement intentions (as discussed later).

Other data sources that have been used to develop a file for starting supply—when licensure data is unavailable—include surveys and national licensure, membership, and registration databases:

- National databases (licensure, membership, or registration)
    - American Medical Association (AMA) Masterfile: continuously updated with a record for each physician who has been licensed in the U.S.
    - American Dental Association (ADA) Masterfile: continuously updated with a record for each dentist who has been licensed in the U.S.
    - National Commission on Certification of Physician Assistants (NCCPA) PA Professional Profile database: continuously updated when PAs renew their certification.
    - Membership files created by individual professional associations
    - National Plan and Provider Enumeration System (NPPES), continuously updated to provide a unique identifier for providers who bill CMS for services provided to Medicare beneficiaries
- Surveys
    - American Community Survey (ACS), updated annually by the U.S. Census Bureau, contains a stratified random sample of the population in each state and lists occupation and employment status
    - Occupational Employment Statistics (OES), updated by the U.S. Bureau of Labor Statistics, collects data on employed individuals via an employer-based survey
    - Occupation/specialty surveys
        - HRSA National Sample Survey of Registered Nurses (NSSRN), last updated in 2008
        - HRSA National Sample Survey of Nurse Practitioners (NSSNP), last updated in 2012

[27] The exclusion/inclusion criteria for developing the starting population files based on licensure data are summarized in the state appendices.

Each of the data sources contains different types of data and has different sample size—ranging from licensure files that contain a complete census of providers in the geographic area of interest, to files that contain a representative sample via survey of providers in the geographic area. State licensure files are usually the most accurate source of data to create the starting supply files, and some of the above data sources are derived from state licensure data.

New Entrants

When modeling at the national level the new entrants are those individuals entering the workforce after completing appropriate training and licensure. When modeling at the state or sub-state level the new entrants reflect both those individuals newly entering the workforce for the first time, as well as individuals who might be migrating mid-career from one geographic area to another.

Each year new entrants are added to the supply file via creation of a "synthetic" population based on the number and characteristics of new entrants to the workforce. For example, if 100 new providers in a given occupation or specialty entered the workforce in a particular year then the model creates 100 new records—one for each person. The age and sex of each new person is generated based on the estimated distribution from recent entrants to the workforce. If, for example, 90% of new entrants to the RN workforce were female then the model generates a random number for each new person using a uniform (0, 1) distribution. The person is designed as male if the random number for that person is less than or equal to 0.1, and otherwise designed as female. A similar process is used to designate the age of the person, and the race/ethnicity for those occupations were this dimension has been added to the supply model.

For state-level analyses, licensure files are the most useful source of information on the number and characteristics of providers entering the workforce. Analyzing several years' data helps provide a sufficient sample size to estimate the annual number and demographics of new entrants. In addition to state licensure files, additional national data sources for information on the number and characteristics of newly trained health providers entering the workforce are listed in Exhibit 15.

Data limitations regarding new entrants presents challenges for modeling future supply of some health occupations. This includes some aide/assistant/paraprofessional occupations where new entrants might enter the workforce through formal or on-the-job training, or where there is no formal licensure process.

Exhibit 15. Data Sources for Number and Characteristics of New Entrants

Profession	Number and Characteristics of New Entrants
All licensed professions	State licensure files (where available)
Nurses (RNs & LPNs)	
Registered nurses	NCLEX; National League for Nursing, http://www.nln.org/researchgrants/slides/topic_nursing_stud_demographics.htm
Licensed practical/vocational nurses	National Council Licensure Examination (NCLEX); Integrated Postsecondary Education Data System (IPEDS)
Oral health professions	
Dentists	American Dental Association Masterfile
Dental hygienists	IPEDS
Physicians	American Medical Association Masterfile, Association of American Medical Colleges
Advanced practice nurses	American Association of Colleges of Nursing
Physician assistants	National Commission on Certification of Physician Assistants; Physician Assistant Education Association
Therapeutic service providers	IPEDS
Rehabilitation service providers	IPEDS
Respiratory care providers	IPEDS
Vision and hearing care providers	IPEDS
Dietitians & nutritionists	IPEDS
Pharmacy professions	IPEDS
Non-physician behavioral health providers	IPEDS
Diagnostic laboratory providers	IPEDS

Labor Force Participation and Attrition

Labor force participation encompasses whether to be in the workforce and level of participation. Clinicians 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 particular geographic area might be the result of emigration (moving away from that geographic location to work elsewhere). The probability of permanent or temporary departure from the workforce varies greatly by occupation and specialty, by clinician demographics, and by external factors such as economic conditions. For those clinicians in the workforce, the HWSM models their level of participation using weekly work hours (though this measure does not capture variation in annual weeks worked that might vary systematically by provider characteristics or other factors that could change over time or across geographic areas). To the extent that determinants of labor force participation might vary over time and geographically, the HWSM tries to simulate the implications of such variation on FTE supply.

In this section we describe efforts to model labor force participation, weekly hours worked, and attrition from the workforce. First, though, we describe modeling hourly wage which is one input used to model labor force participation and hours worked patterns for some health occupations.

Hourly Wages

For some occupations, labor force participation probability and weekly hours worked are estimated for each clinician using prediction equations that include predicted earnings potential as an explanatory variable. In turn, earnings potential (modeled in terms of hourly wages) are modeled as a function of clinician characteristics and external factors as summarized in Exhibit 16 (see also Exhibit A- 10 through Exhibit A- 21 for summary regression results for individual occupations).

The equations to predict hourly wages were estimated separately by occupation using data from the 5-year (2010-2014) American Community Survey for individuals who are currently employed. Hourly wages was calculated by dividing estimated weekly earnings by estimated weekly hours. For each occupation we omit observations from the regression if their calculated hourly wages fall outside the 5th to 95th percentile of wages for that profession (to discard observations whose calculated wages appear to low or too high to be credible).

Included as an explanatory variable is state mean hourly wage for that profession from the BLS Occupational Employment Statistics, 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.[28]

For the occupations modeled, individual wage is highly correlated with state mean wage. Wages tend to increase for those early in their career, but rise more slowly above age 35. Men tend to early higher hourly wages in most occupations. Wages vary by clinician race/ethnicity. Hourly wages rises with the percentage of the population living in suburban areas.

Exhibit 16. OLS Regression Coefficients Predicting Hourly Wages

Parameter	RN	LPN	Dental Hygienist	Physical Therapist	Pharmacist
Intercept	-2.67 **	-0.46	3.48 **	-0.46	-3.36 *
Unemployment rate (state, year) [a]	-0.15 **	-0.03	-0.20 **	0.05	-0.20
State occupation mean hourly wage [a]	0.85 **	0.84 **	0.76 **	0.72 **	0.91 **
Age 35 to 44 [b]	3.87 **	2.15 **	2.65 **	4.47 **	8.73 **
Age 45 to 54 [b]	5.21 **	2.80 **	2.87 **	4.30 **	8.84 **
Age 55 to 59 [b]	5.79 **	3.41 **	3.09 **	3.27 **	8.61 **
Age 60 to 64 [b]	5.74 **	3.43 **	2.71 **	2.77 **	7.83 **
Age 65 to 69 [b]	4.70 **	3.42 **	1.47 *	2.13 *	4.97 **
Age 70+ [b]	2.07 **	2.58 **	0.62	0.19	1.51 *
Male [b]	1.18 **	0.62 **	-2.29 **	1.97 **	1.87 **
Year 2011 [b]	-0.38 **	-0.46 **	-0.33	0.08	-0.52
Year 2012 [b]	0.39 **	-0.44 **	-1.32 **	0.29	-1.30 **
Year 2013 [b]	0.14	-0.40	-1.15 **	0.28	-1.38 **
Year 2014 [b]	-0.29 **	-1.72 **	-0.76	0.28	-2.29 **
Non-Hispanic black [b]	-0.15	0.60 **	-1.01 **	-1.04	-3.92 **
Non-Hispanic other [b]	-0.66 **	0.38 **	-0.10	0.79 *	-1.59 **
Hispanic [b]	1.12 **	-0.82 *	-1.75 **	-2.95 **	-3.90 **
Have nursing baccalaureate degree [b]	2.55 **				
Having nursing graduate degree [b]	4.10 **				
Population % suburban	12.99 **	7.57 **	10.07 **	10.78 **	-4.80

[28] Missouri Economic Research and Information Center. https://www.missourieconomy.org/indicators/cost_of_living/

Population % rural	0.56	1.43 **	3.22 *	3.14 *	-4.22 *
Sample size	150,504	37,294	8,608	10,771	14,488
R-squared	0.12	0.11	0.16	0.19	0.2

Notes: Statistically significant at the 0.01 (**) or 0.05 (*) level. [a] State means by year. [b] Comparison groups are age <35, female, year=2010, non-Hispanic white, and (for RNs only) associate or diploma as highest educational degree.

Activity Status

Activity status for some occupations is modeled using prediction equations derived from ACS (2010-2014) data. This analysis focused on clinicians under age 50 (as the activity status for clinicians over age 50 modeled retirement). The dependent variable was whether the nurse was employed or not employed). Explanatory variables include predicted earnings potential (discussed previously), and the same explanatory variables used to model hourly earnings potential. As summarized in Exhibit 17 for three occupations (see also Exhibit A- 10 through Exhibit A- 21) for summary regression results for individual occupations), the odds of being employed vary by clinician demographics—in particular age. Higher overall unemployment rate slightly raises the odds of RNs being employed (odds rise by 3%), while higher earnings potential is associated with a slight decrease in the odds that RNs are employed.

Exhibit 17. Odds Ratios Predicting Probability Active

Parameter	RN (n=89,370) Odds Ratio and CI			LVN (n=23,348) Odds Ratio and CI			Pharmacist (n=9,556) Odds Ratio and CI		
Unemployment rate (state, year) [a]	1.03	1.01	1.05	0.99	0.96	1.03	1.08	1.00	1.16
Predicted hourly wage	0.97	0.96	0.99	1.01	0.99	1.04	0.98	0.96	1.00
Age 30-34	0.69	0.63	0.77	1.00	0.87	1.16	1.97	1.44	2.69
Age 35-39	0.89	0.79	1.00	1.08	0.92	1.26	1.67	1.19	2.33
Age 40 to 44	0.97	0.86	1.08	1.10	0.94	1.29	2.91	1.96	4.33
Age 45 to 49	1.12	0.99	1.27	1.08	0.92	1.27	3.63	2.31	5.70
Male [b]	0.71	0.58	0.87	1.39	1.03	1.88	1.32	0.97	1.79
Age 30-34 * male	2.20	1.59	3.06	1.36	0.77	2.41	2.17	1.05	4.45
Age 35-39 * male	2.81	1.96	4.02	1.06	0.62	1.81	3.52	1.69	7.35
Age 40 to 44 * male	2.63	1.87	3.70	1.31	0.76	2.27	1.72	0.80	3.69
Age 45 to 49 * male	1.94	1.38	2.74	0.79	0.48	1.29	1.71	0.73	4.01
Year 2011 [b]	0.93	0.84	1.03	0.89	0.76	1.04	1.28	0.94	1.74
Year 2012 [b]	0.92	0.83	1.02	0.87	0.74	1.02	1.20	0.89	1.64
Year 2013 [b]	0.93	0.84	1.05	0.91	0.76	1.08	1.62	1.15	2.26
Year 2014 [b]	0.97	0.85	1.10	0.80	0.66	0.98	1.86	1.25	2.75
Non-Hispanic black [b]	1.32	1.17	1.49	1.42	1.24	1.62	1.19	0.72	1.97
Non-Hispanic other [b]	1.23	1.10	1.37	0.91	0.77	1.09	0.75	0.59	0.96
Hispanic [b]	1.38	1.19	1.60	1.04	0.88	1.22	0.72	0.46	1.12
Have nursing baccalaureate degree [b]	0.98	0.91	1.05						
Having nursing graduate degree [b]	0.91	0.80	1.03						
Population % suburban	2.27	1.33	3.89	1.26	0.54	2.95	1.36	0.19	9.69
Population % rural	0.77	0.52	1.15	0.47	0.26	0.84	2.53	0.63	10.20

Notes: Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50.

Hours Worked Patterns

The microsimulation model estimates weekly hours worked for each individual and simulates how hours worked change over time as the clinician ages or changes in other workforce determinants. Hours worked patterns vary based on many factors: occupation/specialty, provider characteristics, economic conditions, and geographic location. Hours worked is converted to FTE levels by dividing the hours worked for each provider by average hours worked in the profession. Patterns of hours worked were calculated differently by occupation based on data availability. Where possible, we used regression analysis (with Ordinary Least Squares regression) to estimate the effect of workforce determinants on weekly hours worked.

Physicians

For physicians, the hours worked regression included specialty, age group, sex, and age-by-sex interaction terms as dependent variables. Regression analysis (Exhibit 18) using Florida's 2012-2013 bi-annual Physician Licensure Workforce Survey (n=18,016), restricted to physicians who reported working at least 8 hours per week in professional activities. The Florida survey has been used for national physician workforce projections, but ongoing research is exploring the use of data from additional states. Regression analysis using survey data from South Carolina A similar analysis of Maryland physician survey data was conducted and yielded similar patterns in hours worked trends by age, sex, and specialty—though the Maryland hours worked patterns were slightly lower.

Exhibit 18 summarizes regression results for physicians. The results show differences in weekly patient care hours worked by specialty. For example, Florida physicians in allergy & immunology work about 11 hours fewer per week than those in vascular surgery (the comparison specialty) whereas South Carolina physicians in allergy & immunology work about 11.2 fewer hours per week relative to vascular surgeons. Hours worked begin to decline after age 55. Female physicians on average work fewer hours than their male counterparts. Estimated by combining the numbers for Female and the Female-Age interaction terms, female physicians age 50 to 54 in Florida work about 8.8 fewer hours per week than their male peers (6.3 fewer hours for female physicians in South Carolina relative to their male peers).

Exhibit 18. OLS Regression of Physicians' Weekly Patient Care Hours Worked

Parameter	Florida Hours		South Carolina Hours	
Intercept	49.5	**	35.5	**
Specialty (Vascular Surgery is reference category)				
Allergy & Immunology	-11.0	**	-11.2	**
Anesthesiology	-2.6		0.8	
Cardiology	0.5		1.9	
Colon & Rectal Surgery	-0.9		5.1	
Critical Care Medicine	-0.8		-0.7	
Dermatology	-10.8	**	-10.8	**
Emergency Medicine	-10.6	**	-10.4	**
Endocrinology	-3.7		-7.6	**
Gastroenterology	-0.8		2.5	
Family Medicine	-6.9	**	-7.2	**
General Internal Medicine	-3.5	*	-3.7	
General Surgery	0.5		2.7	
Geriatric Medicine	-6.7	**	-9.0	**
Hematology & Oncology	-1.3		-4.3	
Infectious Diseases	-2.4		-8.6	**
Neonatal & Perinatal Medicine	4.8		-4.7	

Parameter	Florida Hours		South Carolina Hours	
Nephrology	2.7		-0.6	
Neurological Surgery	1.5		-3.1	
Neurology	-3.9	*	-5.9	*
Obstetrics & Gynecology	-1.4		1.9	
Ophthalmology	-8.8	**	-8.8	**
Orthopedic Surgery	-3.7	*	-4.0	
Otolaryngology	-5.4	**	-4.8	
Pathology	-8.3	**	-10.3	**
Pediatrics	-6.8	**	-7.7	**
Physical Medicine & Rehab	-6.5	**	-10.3	**
Plastic Surgery	-7.8	**	-4.9	
Preventive Medicine	-14.2	**	-29.2	**
Psychiatry	-8.1	**	-13.1	**
Pulmonology	3.0		-2.9	
Radiation Oncology	-6.0	**	-7.9	*
Radiology	-5.4	**	-4.9	*
Rheumatology	-3.4		-8.8	
Thoracic Surgery	1.7		1.2	
Urology	-0.5		3.4	
Age (70+ is reference category)				
Age <40	11.4	**	11.1	**
Age 40 to 44	11.7	**	14.1	**
Age 45 to 49	11.6	**	16.0	**
Age 50 to 54	12.0	**	16.1	**
Age 55 to 59	11.0	**	15.2	**
Age 60 to 64	9.7	**	14.1	**
Age 65 to 69	5.9	**	7.7	**
Female	-3.3	**	2.1	
Female x Age <40	-4.1		-6.2	*
Female x Age 40 to 44	-6.0	*	-8.7	**
Female x Age 45 to 49	-5.9	*	-10.9	**
Female x Age 50 to 54	-5.5	*	-8.4	**
Female x Age 55 to 59	-2.5		-9.5	**
Female x Age 60 to 64	-3.5	*	-8.1	*
Female x Age 65 to 69	-2.7		-4.7	
Florida summary statistics: n=18,016; R^2=0.101; Mean hours worked=42.5				
South Carolina summary statistics: n=9,276; R^2=0.18; Mean hours worked=41.8				

Note: Statistically significant at the 0.01 (**) or 0.05 (*) level.

Similar analyses were conducted for PAs and APRNs, using the 2013 NCCPA licensure files and HRSA's National Sample Survey of Nurse Practitioners (2012), respectively.

Other Health Occupations

The hours worked regressions for other health occupations modeled analyzed ACS data (2010-2014) for employed clinicians similar to the regression specifications for modeling hourly wages. Dependent variables included clinician characteristics, state overall unemployment rate, and estimated hourly earnings potential.

Exhibit 19 summarizes regression output for select occupations (with Exhibit A- 10 through Exhibit A- 21) containing summary regression results for individual occupations). For all occupations, weekly hours worked decline rapidly from age 65 onward. On average, male RNs work 2.78 more hours than their female counterparts, Hispanic RNs work 2.28 hours more than non-Hispanic RNs, RNs with a baccalaureate or graduate degree work 1.43 hours more than RNs with an associate or diploma degree, and RNs in states with a larger proportion of the population residing in rural areas tend to work more hours. Hours worked per week by RNs rises slightly with the unemployment rate.

Exhibit 19. OLS Regression Coefficients Predicting Weekly Hours Worked for Select Occupations

Parameter	RN	LPN	Dental Hygienist	Physical Therapist	Pharmacist
Intercept	35.15 **	34.44 **	33.15 **	33.57 **	33.23 **
Unemployment rate (state, year) [a]	0.05 *	0.05	-0.06	0.06	-0.03
Predicted wage	0.01	0.04	-0.06 *	0.11 **	0.06 **
Age 35 to 44 [b]	0.26 **	1.85 **	-1.49 **	-2.70 **	1.13 **
Age 45 to 54 [b]	1.20 **	2.04 **	-1.36 **	-1.56 **	1.80 **
Age 55 to 59 [b]	0.88 **	1.52 **	-2.34 **	-1.14 **	1.89 **
Age 60 to 64 [b]	-0.31 **	0.35	-3.06 **	-1.92 **	0.20
Age 65 to 69 [b]	-4.54 **	-4.33 **	-4.62 **	-5.96 **	-4.38 **
Age 70+ [b]	-8.57 **	-7.42 **	-8.79 **	-10.25 **	-10.62 **
Male [b]	2.78 **	1.77 **	5.53 **	6.50 **	3.79 **
Year 2011 [b]	0.14	-0.02	0.08	-0.42	0.36
Year 2012 [b]	0.21 *	0.27	0.27	-0.42	0.30
Year 2013 [b]	0.30 **	0.17	0.01	-0.38	0.73 *
Year 2014 [b]	0.38 **	0.22	0.58	0.03	0.48
Non-Hispanic black [b]	-0.24 **				
Non-Hispanic other [b]	1.56 **				
Hispanic [b]	2.28 **	1.05 **	5.02 **	1.24 *	1.20 **
Have nursing baccalaureate degree [b]	1.43 **	1.16 **	1.17 *	0.74 *	0.51 *
Having nursing graduate degree [b]	1.43 **	1.04 **	2.36 **	1.26 *	0.25
Population % suburban	0.73	-2.09 *	7.24 **	-1.75	-6.97 **
Population % rural	1.41 **	1.96 **	-1.69	-1.16	2.05
Sample size	150,504	37,294	8,608	10,771	14,488
R-squared	0.04	0.04	0.04	0.10	0.08

Notes: Statistically significant at the 0.01 (**) or 0.05 (*) level. [a] State means by year. [b] Comparison groups are age <35, female, year=2010, non-Hispanic white, and (for RNs only) associate or diploma as highest educational degree.

Retirement

The approach to modeling retirement differs by occupation depending on data availability. When estimating retirement patterns based on survey data, attrition patterns need to incorporate mortality probability. Mortality rates came from the Centers for Disease Control and Prevention (CDC) and are specific to each age-gender combination.[29] Johnson et al. found that age-adjusted mortality rates for occupational and technical

[29] Arias E. United States life tables, 2008. National vital statistics reports' vol 61 no 3. Hyattsville, MD: National Center for Health Statistics; 2012.

specialties are ~25% lower than national rates for men and 15% lower for women through age 65, so mortality rates for physicians under age 65 were adjusted downward accordingly.[30]

The supply model assigns each person an attrition probability based on age, sex, and occupation/specialty. This probability is then added to the age and gender-based mortality probability, resulting in a final attrition probability. This probability is then compared with a random number between 0 and 1 (using a uniform distribution) to simulate whether the person leaves the workforce each year. For example, if an active clinician age 66 has a 20% probability of retiring by age 67, then if the random number is below 0.2 the person is modeled as retiring. Else, that person is modeled as still active at age 67 and the simulation repeats each year as the person ages through simulated retirement.

Physician Attrition Patterns

There is a paucity of recent information on retirement patterns of physicians. Few surveys collect information on retirement intentions or retirement age; state licensure files often have small sample size for older physicians in individual specialties; and national surveys like ACS do not indicate physician specialty. The retirement rates used in the HWSM were estimated using survey data from the Florida bi-annual physician survey (2012-2013 data) that asks about intention to retire in the upcoming five years. Derived retirement patterns are similar to estimates derived from analysis of the AAMC's 2006 Survey of Physicians over Age 50 (which collected information on actual retirement age of retired physicians, or age expecting to retire for those physicians still active).

While women in the survey often indicated a slightly earlier intention to retire, once factoring in the higher mortality rates for men the overall retirement rates for men and women appear similar (Exhibit 20). Among 100 physicians active in the workforce at age 50, by age 60 approximately 80 will still be active. By age 70 approximately 30 will still be active. When taking into consideration that average hours worked decline with age (as discussed in a later section), the number of FTE physicians above age 70 is much lower than indicated by retirement patterns alone.

[30] Johnson NJ, Sorlie PD, Backlund E. The impact of specific occupation on mortality in the US National Longitudinal Mortality Study. Demography; 1999 Aug; 36:355-367.

Exhibit 20. Physician Retirement Patterns

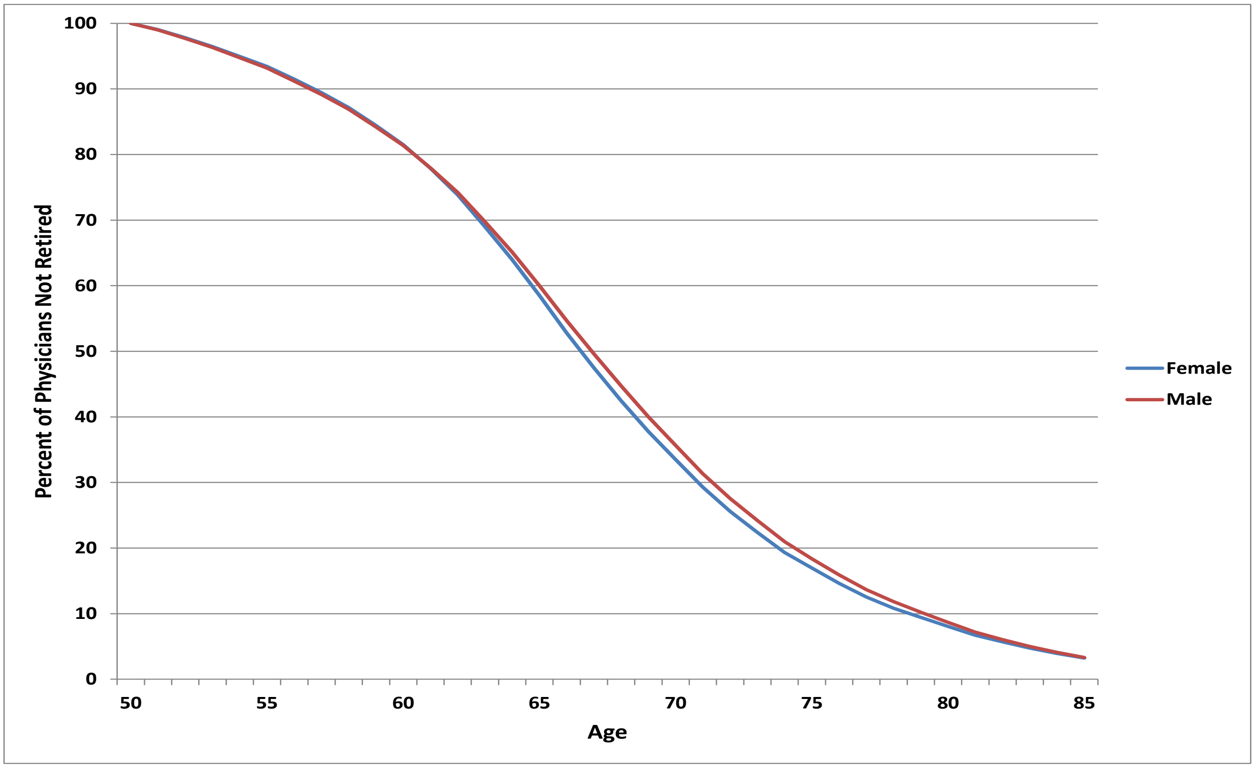
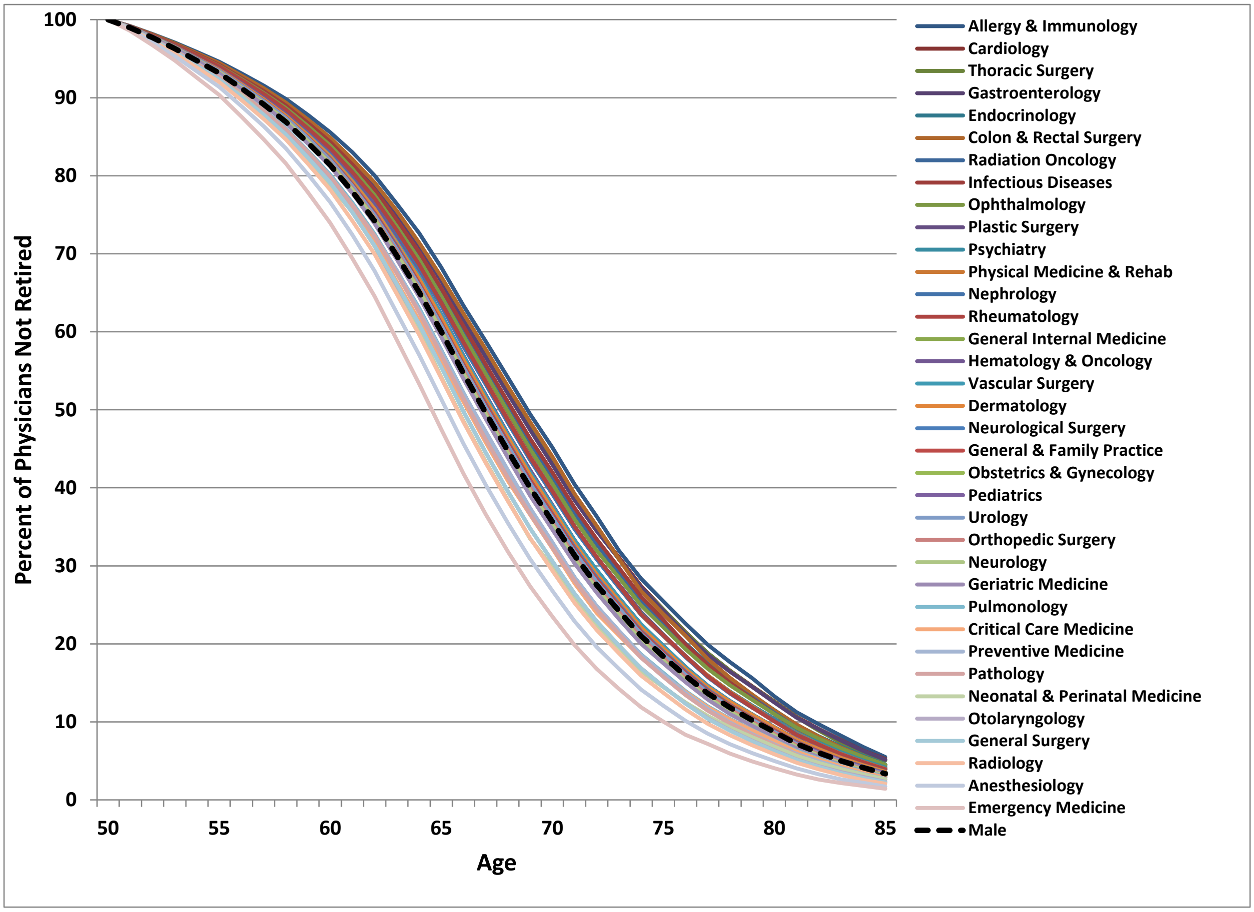


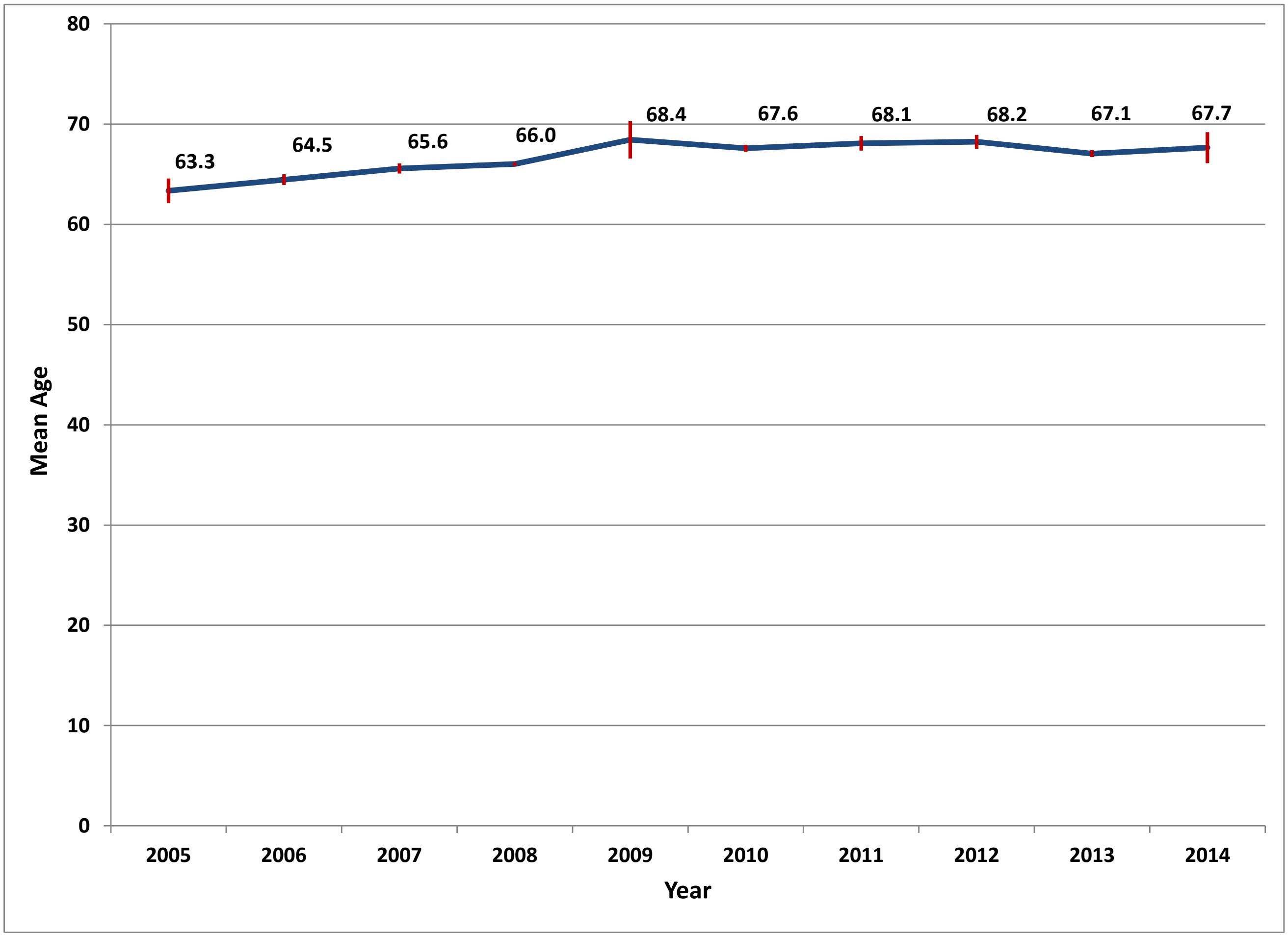
Exhibit 21 shows estimated overall attrition patterns for male physicians by specialty, with some specialties such as emergency medicine experiencing earlier attrition relative to other specialties. For example, by age 65 approximately 65% of allergists & immunologists are still active, while only 50% of emergency physicians are still active.

Exhibit 21. Probability Male Physician is Still Active by Specialty and Age



These patterns suggest that the median age of retirement is ~67-68 years old (i.e., about half retire before that age, and half retire after). This estimate of median retirement age is similar to the estimates of the mean age of retiring physicians (Exhibit 22) that the AAMC Center for Health Workforce estimates has been approximately age 68 from 2009 to 2014 (up from approximately age 63 in 2005). Supply projection scenarios described later include modeling the sensitivity of projections if physicians were to increase or decrease average retirement age.

Exhibit 22. Mean Age of Retiring Physicians (age 50+)



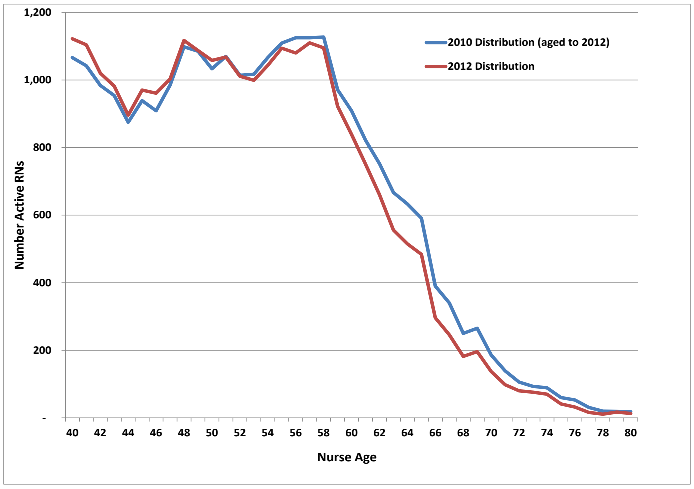
Source: AAMC analysis of American Community Survey. Vertical lines represent standard errors for individual-year estimates.

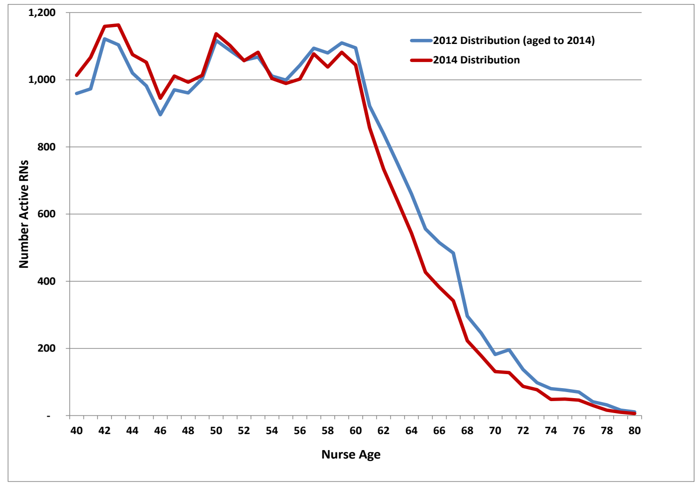
Nurse Retirement Patterns

Multiple approaches have been explored and used to estimate nurse retirement patterns. ACS only captures one's occupation if he or she has been in the workforce within the past five years. Hence, labor force participation rates by occupation estimated from ACS are conditional on the person being in the workforce within the past five years. ACS also captures highest educational attainment. Prior to 2016, IHS used ACS-derived labor force participation rates by age and sex for RNs age 50 and younger. However, for RNs over age 50 IHS used labor force participation rates for college educated men and women over age 50 as a proxy for labor force participation rates for male and female RNs over age 50 with similar education level (i.e., with an associate degree, a baccalaureate degree, or a graduate degree).

In 2015, IHS analyzed licensure data from South Carolina (SC) to analyze attrition rates from SC's workforce. Multiple years of licensure data (2010, 2012, and 2014) were analyzed. The research files used do not contain an individual identifier to link nurses across years. Therefore, IHS compared the age distribution of active RNs in SC in 2012 compared to the expected age distribution in 2012 if all RNs active in 2010 remained active (Exhibit 23). Similarly, the Exhibit compares the age distribution of RNs active in 2014 to the age distribution that would be expected in 2014 if all active RNs in 2012 remained active. In both 2-year comparisons for nurses age 50 and older there were fewer active nurses in 2012 and 2014 than would be expected if there had been no attrition in the previous two years (as reflected by the red line being below the blue line for nurses age 50 and older). The gap between the red and blue lines reflects net attrition from the workforce (including both retirement and net migration out of the state). Estimates of the number of RNs leaving the workforce at each age were similar between (a) 2010 and 2012 and (b) 2012 and 2014. Consequently, we combined data across all four years (2010-2014) to estimate retirement patterns. IHS conducted a similar analysis using Texas licensure data for RNs and found similar attrition patterns.

Exhibit 23. Comparison of South Carolina RN Licensure Files: 2010 & 2012, 2012 & 2014

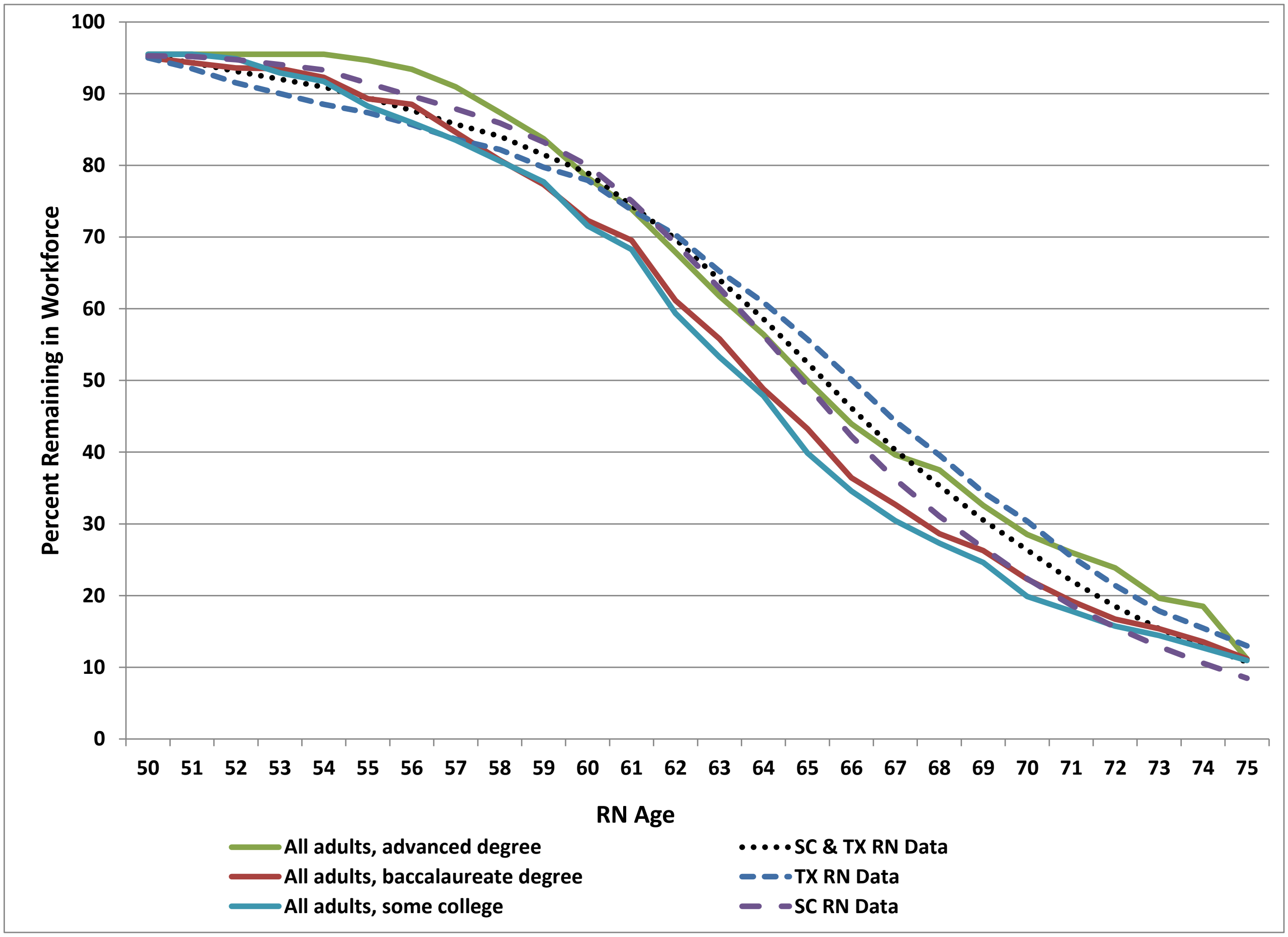




The calculated retirement patterns using South Carolina and Texas licensure files are presented in Exhibit 24 for comparison against the retirement patterns calculated from ACS data and used as a proxy for retirement patterns of associate/diploma-trained RNs, baccalaureate-level RNs, and RNs with a graduate degree.

The approach used to estimate retirement patterns for RNs was also used to estimate retirement patterns for LPNs. The HWSM currently uses retirement patterns for primary care physicians as a proxy for the retirement patterns of APRNs due to data limitations—including small number of older APRNs in available data sources to estimate retirement patterns.

Exhibit 24. Estimated Retirement Patterns for Nurses



Retirement Patterns of Other Health Providers

For physician assistants, the HWSM currently uses retirement patterns for primary care physicians as a proxy. (Similar to APRNs, there are few older PAs in available data sources). Analysis of South Carolina licensure data for PAs comparing age distributions of active PAs across years was explored to estimate attrition patterns for PAs, but the number of older PAs in South Carolina is relatively small. However, comparison of these derived attrition patterns to estimate for primary care physicians indicates that PAs under age 63 are less likely to be retired relative to primary care physicians while PAs older than age 63 are more likely to be retired relative to primary care physicians.

For other health occupations, HWSM uses retirement patterns estimated from ACS data by education level as a proxy for retirement patterns of the individual occupation (see Exhibit 24).

Geographic Migration

Migration patterns of clinicians across states is an ongoing area of research for the HWSM. Cross-state migration can happen at the start of one's career upon completion of training, or can occur mid-career. The probability of cross-state migration and the factors influencing such migration vary by occupation and by state. Higher-paying occupations like physicians are more likely to be in a national labor market relative to lower-paying health occupation (from which recruiters might look locally). However, occupations with high rates of self-employed (e.g., dentists or physicians) are probably less likely to move mid-career, after establishing a practice, relative to occupations that are likely employed and thus more mobile.

One scenario modeled is based on the assumption that areas of the country experiencing faster growth in demand for health care services will also experience faster growth in provider supply relative to areas of the country experiencing slower growth in demand for services. This approach has been applied when modeling demand for physicians, dentists, and RNs. The approach consists of the following for the occupation or medical specialty of interest:

1. Estimate the projected growth in demand in each state over time (e.g., between 2014 and 2025).
2. Estimate the number of retirements in each state over the same time period.
3. Add each state's growth in demand to the estimate of retirements to estimate total new workers required.
4. Sum total new requirements across states and calculate each state's share of total requirements.
5. Use this distribution of requirements as a proxy for how new workers will distribute across states.

Each new entrant to the workforce is assigned a state using this calculated distribution under the assumption that new graduates will migrate to those geographic locations where growth in demand or retirements creates opportunities for employment (but allowing current mal-distribution of health professionals to persist). For example, faster growing states are anticipated to attract a growing proportion of the nation's new health professionals while slower growing states are likely to attract a smaller proportion than historical patterns. This topic is an area for continued research.

Scenarios

HWSM can model scenarios based on changes in supply drivers—namely, number of new entrants to the workforce; changes in labor force participation or hours worked patterns; and changes in retirement patterns.

- **New graduates**. The baseline supply projections reflect the anticipated growth in annual number of workers trained each year under current trends. This might reflect the number trained in the most recent year or, in the case of PAs or other rapidly growing occupations, assumptions about the increase in training capacity as announced new programs start graduating new workers. High growth scenarios might model, for example, the implications of training 10% more providers. Low growth scenarios might model the implications of training fewer providers.
- **Delayed and Early Retirement**: There have been some indications, as reported by the Bureau of Labor Statistics, that older workers have recently been delaying retirement.[31] A scenario simulating a two-year delay and two year-earlier trend in retirements can make it easier to understand the effect this may have on the health workforce.
- **Hours Worked Cohort Effects:** It is conceivable that hours worked patterns for physicians joining the workforce in the coming years may be systematically different from current patterns. For example, there has been some research that suggests younger workers may prefer to work fewer hours than workers the same age in 1980.[32] A scenario which modeled a decreased hours worked for younger cohorts could explore the potential effects of this trend.

[31] Toossi M. Labor Force Projections to 2010: A More Slowly Growing Workforce. *Monthly Labor Review*. 2012;43-64.

[32] *The Complexities of Physician Supply and Demand: Projections from 2013 to 2025.* Prepared for the Association of American Medical Colleges. Washington, DC: Association of American Medical Colleges; 2015. https://www.aamc.org/download/426242/data/ihsreportdownload.pdf

IV. MODELING WORKFORCE IMPLICATIONS OF STATEGIES TO PREVENT OR MANAGE CHRONIC DISEASE

The Disease Prevention Microsimulation Model (DPMM) is designed to model the health and economic implications of interventions to improve population health. Population health management plays an important role in modeling future demand for health care services and providers—with lifestyle indicators and health-related behavioral related to smoking, diet, physical activity, and other activities (e.g., preventative screenings, vaccinations, and early treatment) linked to patient health. Improved lifestyle choices and other preventative care can help prevent, delay onset, or reduce severity of many chronic conditions such as asthma, diabetes, heart disease, and cancer.[33]

The DPMM has been used in recent engagements to model the implications of lifestyle counseling among overweight and obese adults with risk factors for cardiovascular disease and diabetes; improved control of blood pressure, cholesterol, and blood glucose levels through medication; tobacco cessation; and screening and early treatment for select preventable conditions.[34] Detailed documentation of the DPMM is available elsewhere.[35]

An interdependent relationship exists between the health workforce and prevention efforts to improve health.

- Many prevention interventions are provided by health workers (e.g., screening, counseling, and providing preventative services like vaccinations) thus increasing demand for the occupations that provide such services.
- Reducing prevalence or severity of chronic conditions and adverse medical events through prevention reduces demand for clinicians who provide those services (and can shift demand to lower-acuity care delivery settings).
- Preventing or delaying onset of chronic disease can reduce mortality, and longer life expectancy increases patient use of other health care services.

The DPMM uses a Markov Chain Monte Carlo simulation approach to model likelihood and timing of disease onset for each person in a representative sample of the population of interest. Using data from sources such as the Behavioral Risk Factor Surveillance System (BRFSS) and National Health and Nutrition Examination Survey (NHANES), a representative sample of the population of interest is created. This population file contains the same variables used in the HDMM, as well as some additional clinical variables specific to the DPMM. Shared variables between HDMM and DPMM include demographics (age, sex, race/ethnicity), insurance type (Medicare, Medicaid, private, uninsured), current smoking status, body weight status (normal, overweight, obese), presence of chronic disease (diabetes, heart disease, hypertension, asthma, arthritis), and history of adverse medical events (cancer, myocardial infarction, stroke). In addition, the DPMM requires additional clinical information such as body mass index, systolic blood pressure, cholesterol, and blood

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[33] National Prevention Strategy: America's Plan for Better Health and Wellness. http://www.cdc.gov/Features/PreventionStrategy/

[34] Su W, Huang J, Chen F, Iacobucci W, Dall TM, Perreault L. Return on Investment for Digital Behavioral Counseling in Patients with Prediabetes and Cardiovascular Disease. Preventing Chronic Disease. 2016; 13; ;150357.

Su W, Huang J, Chen F, Iacobucci W, Mocarski M, Dall TM, Perreault L. Modeling the Clinical and Economic Implications of Obesity using Microsimulation. *Journal of Medical Economics*. 2015: 1-12.

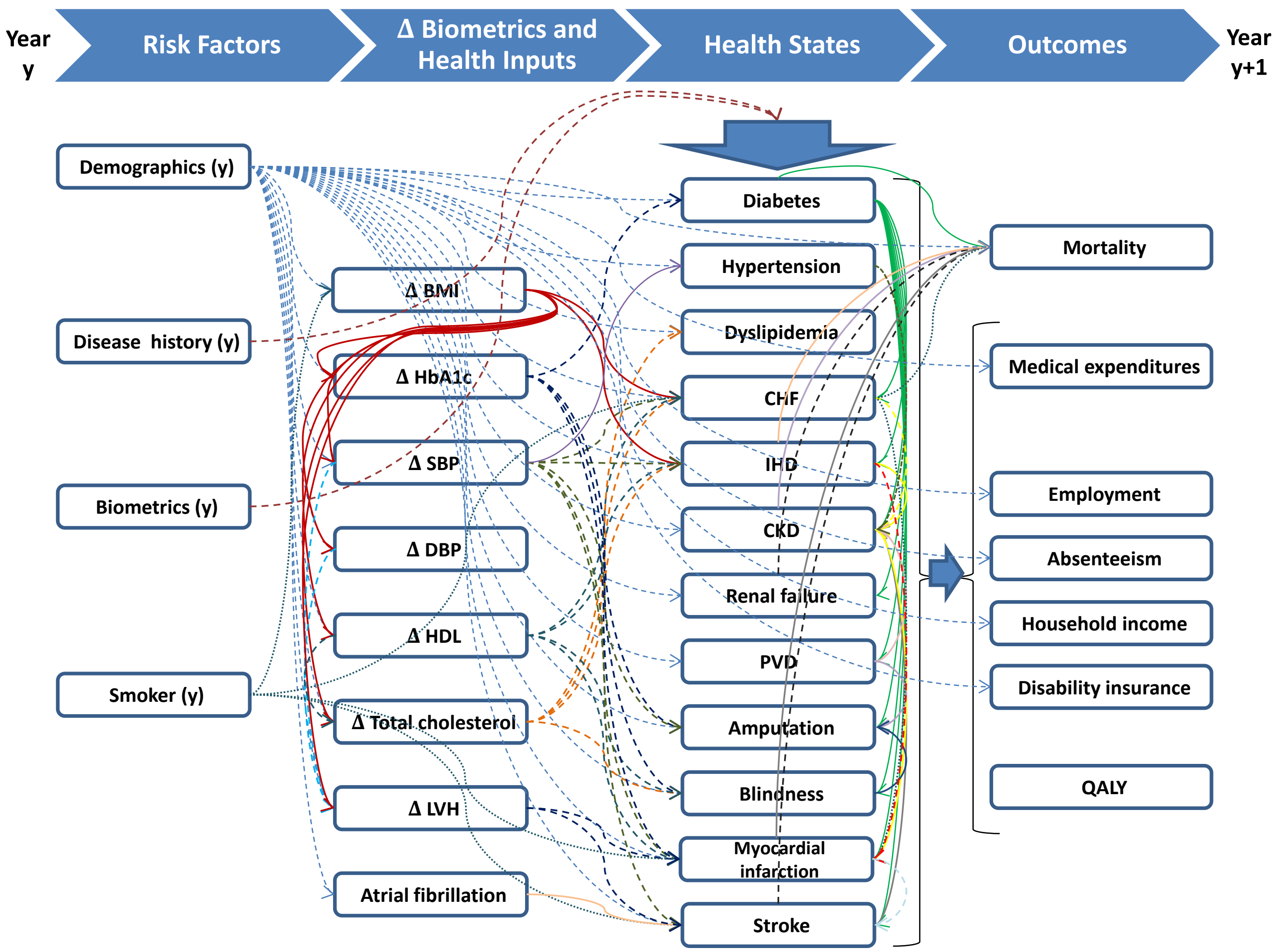
Dall TM, Storm MV, Semilla AP, Wintfeld N, O'Grady M, and Narayan VKM. Value of Lifestyle Intervention to Prevent Diabetes and Sequelae. *American Journal of Preventive Medicine*. 2015 Mar;48(3):271-280.

Semilla AP, Chen F, and Dall TM. Reductions in Mortality Among Medicare Beneficiaries Following the Implementation of Medicare Part D. *American Journal of Managed Care*. 2015 Jul; 21(9)S165-171.

[35] IHS Life Sciences Disease Prevention Microsimulation Model. 2016. https://www.ihs.com/products/healthcare-modeling.html

glucose levels; and the presence of other diseases. Exhibit 25 provides an overview of the diabetes component of the DPMM, with each arrow below showing how patient characteristics and outcomes are linked. In a particular year (y), a person's health risk factors and biometric readings can affect how biometric levels change over the year as the person ages (to year y+1). Changing biometrics (as well as the other risk factors) are linked to the probability of various health states (e.g., onset of diabetes or heart disease). The health states are also linked—e.g., diabetes is an independent risk factor for heart disease in addition to sharing common risk factors such as obesity and smoking. The presence and severity of chronic disease affect patient mortality and other outcomes modeled.

Exhibit 25. Overview Diagram of Diabetes Component of DPMM

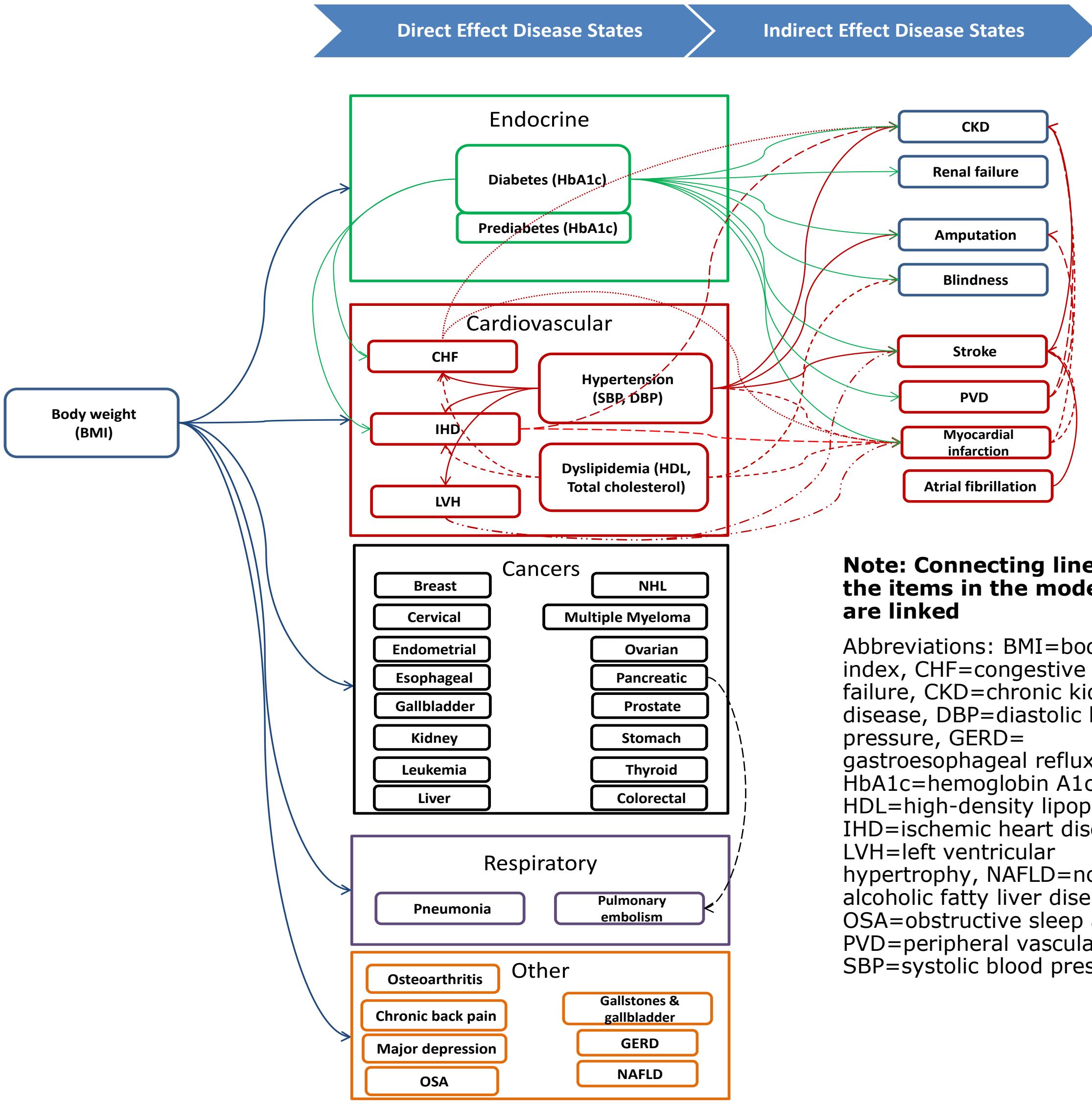


Note: Connecting lines show the items in the model that are linked

Abbreviations: BMI=body mass index, CHF=congestive heart failure, CKD=chronic kidney disease, DBP=diastolic blood pressure, HbA1c=hemoglobin A1c, HDL=high-density lipoprotein, IHD=ischemic heart disease, LVH=left ventricular hypertrophy, PVD=peripheral vascular disease, SBP=systolic blood pressure.

Similarly, Exhibit 26 illustrates how a biometric variable like body mass index (BMI) is linked to various cancers and endocrine, cardiovascular, respiratory, and other medical conditions. Many of these medical conditions have independent effects on disease onset risk for other medical conditions.

Exhibit 26. Overview Diagram of Body Weight in the DPMM



Note: Connecting lines show the items in the model that are linked

Abbreviations: BMI=body mass index, CHF=congestive heart failure, CKD=chronic kidney disease, DBP=diastolic blood pressure, GERD= gastroesophageal reflux disease, HbA1c=hemoglobin A1c, HDL=high-density lipoprotein, IHD=ischemic heart disease, LVH=left ventricular hypertrophy, NAFLD=non-alcoholic fatty liver disease, OSA=obstructive sleep apnea, PVD=peripheral vascular disease, SBP=systolic blood pressure.

The patient-level output from the DPMM can then be run through the HDMM to simulate how the presence of chronic conditions affects patient use of health care services and the setting where that care is provided.

V. MODEL VALIDATION, STRENGTHS, AND LIMITATIONS

Validation Activities

Validation activities continue on an ongoing basis during model development and refinement, as a long term process evaluating the accuracy of the model and making refinements as needed. For each of four primary types of validation deployed, key short term and long term activities include the following:

- **Conceptual validation**: Through reports, presentations at professional conferences and submission of peer-reviewed manuscripts the three models described here (HDMM, HWSM, and DPMM) continue to undergo a peer-review evaluation of its theoretical framework. Contributors to these models include health economists, statisticians and others with substantial modeling experience; physicians, nurses, behavioral health providers and other clinicians; health policy experts; and professionals in management positions with health systems. Conceptual validation requires transparency of the data and methods to allow health workforce researchers and modelers to critique the model. This report is an attempt to increase the transparency of these complex workforce projection models where work is ongoing to improve the theoretical underpinnings, methods, assumptions, and other model inputs.
- **Internal validation**: The model runs using SAS software. As new capabilities are added to the model and data sources updated, substantial effort is made to ensure the integrity of the programming code. Internal validation activities include generating results for comparison to published statistics used to generate the model (e.g., ensuring that population statistics for the input files are consistent with published statistics).
- **External validation**: Presenting findings to subject matter experts for their critique is one approach to externally validate the model. Intermediate outputs from the model also can be validated. For example, the HDMM has been used to project demand for health care services for comparison to external sources not used to generate model inputs. Results of such comparisons across geographic areas indicate that more geographic variation in use of health care services occurs than is reflected geographic variation in demographics, presence of chronic disease, and health risk factors such as obesity and smoking.
- **Data validation**: Extensive analyses and quality review have been conducted to ensure data accuracy as model data inputs were prepared. Most of the model inputs come from publically available sources (e.g., MEPS, BRFSS, ACS)—with the exception that licensure data used in the model is often proprietary to each state licensure board and purchased data from the American Medical Association and other groups has sometimes been used for certain studies.

Model Strengths

The main strengths of the three models include use of recent data sources and a sophisticated microsimulation approach that has substantial flexibility for modeling changes in care use and delivery by individuals or by the health care system. Compared to population-based modeling approaches used historically, these microsimulation models take into account more detailed information on population characteristics and health risk factors when making national and state-level demand projections. For example, rates of disease prevalence and health related risk factors and household income can vary significantly by geographic area. Such additional population data can provide more precise estimates of service demand at State and county levels compared to models that assume all people within a demographic group use the same level of services.

HDMM simulates care use patterns by delivery setting. Certain populations have disproportionately high use of specific care delivery settings (e.g., emergency care) and lower use of other settings. Setting-specific information on patient characteristics and use rates provides insights for informing policies that influence the way care is delivered. Because the microsimulation approach uses individuals as the unit of analysis, the HDMM can simulate demand for health care services and providers to care for populations in low income categories, populations in select underserved areas, or populations with certain chronic conditions. Using individuals as the unit of analysis creates flexibility for incorporating evidence-based research on the implications of changes in technology and care delivery models that disproportionately affect subsets of the population with certain chronic conditions or health-related behaviors and risk factors. This information also leads to more accurate projections at state and local levels.

The microsimulation approach also provides added flexibility for modeling the workforce implications of changes in policy and emerging care delivery models under ACA, important areas of ongoing research.

HWSM Limitations

Many limitations of the workforce models stem from current data limitations. One limitation of the BRFSS as a data source for modeling demand is that as a telephone-based survey it tends to exclude people in institutionalized settings who typically do not own telephones. Hence, when creating the population files that underlie the demand projections BRFSS data is combined with National Nursing Home Data.

Other current data limitations associated with these models include:

- Data to better understand migration patterns of health professions at national and sub-state levels.
- Information on the influence of provider and payer networks on consumer service demand and migration patterns.
- Information on how care delivery patterns might change over time in response to the ACA and other emerging market factors.
- Provider retirement patterns.

Areas of Ongoing and Future Research

The following are areas of ongoing research.

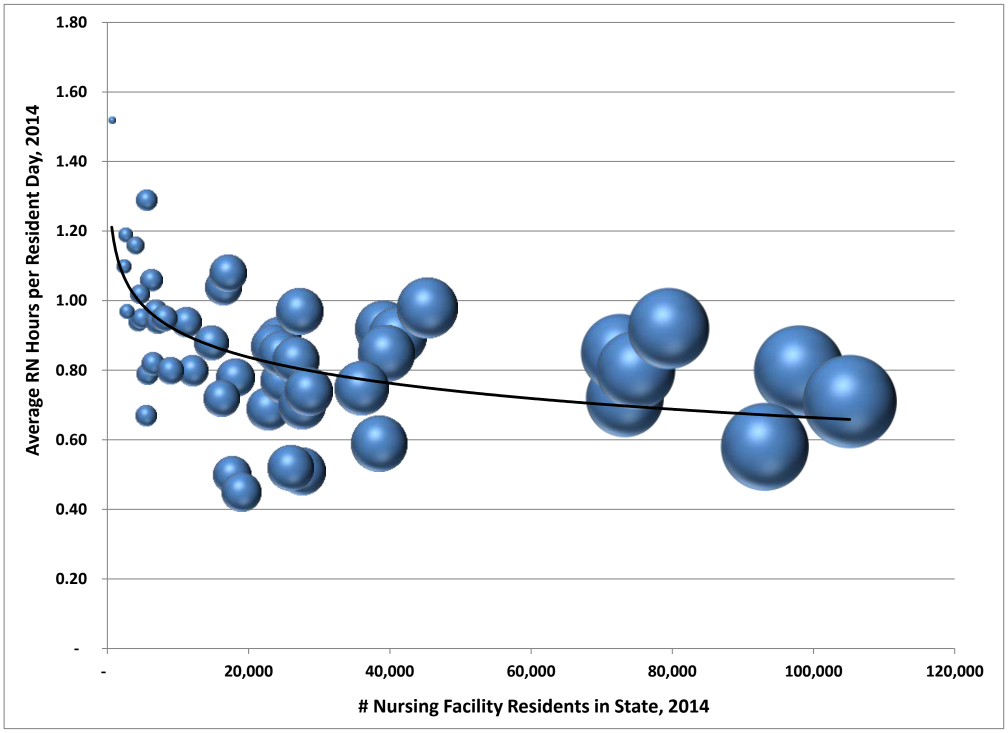
- **Impacts of changes in the healthcare delivery system:** Current efforts using the model include analyzing the potential workforce implications of New York's Delivery System Reform Incentive Payment (DSRIP) Program to restructure the health care delivery system (with a focus on the Medicaid program). Individual DSRIP initiatives being modeled include:
    - System Transformation
        - Create integrated delivery systems that are focused on evidence-based medicine / population health management
        - Expand access to community primary care services and develop integrated care teams to meet needs of higher risk patients

        - Reduce avoidable emergency department use by expanding availability of primary care practitioners, extending hours and availability of patient navigators
        - Implementation of observational programs in hospitals
        - Reduce 30 day readmissions for chronic conditions
        - Patient activation to expand community based care
        - Development of community-based health navigation services
        - Create medical villages
    - Clinical Improvement Projects
        - Co-location of behavioral health providers at primary care sites
        - Disease management for cardiovascular disease, diabetes, and asthma
        - Increase access to palliative care
    - Population-wide Projects
        - Strengthen mental health/substance abuse infrastructure
        - Promote tobacco use cessation, especially among low income populations and those with poor mental health

- **Evolving technology:** Currently, limited data are available to model potential impacts on health professions demand associated with telemedicine, health IT and other new and evolving medical and IT technologies, particularly as these technologies intersect with emerging models of care. This is an important area for future research. While potentially reducing service utilization and demand in some settings (e.g., hospitals), new technologies might support greater use of services and providers practicing in other care settings (e.g., telemedicine) and has the potential to increase or decrease demand depending upon the specific technologies deployed.
- **Prediction equations for staffing:** Ongoing research is exploring the use of prediction equations for staffing, rather than national ratios, to reflect other determinants of nursing (e.g., efficiencies associated with patient volume, wages, and the availability of other providers. For example, states with fewer nursing facility residents report higher average RN hours per resident day (Exhibit 27). This could reflect that states with smaller populations (or states more sparsely populated) tend to have smaller nursing facilities but still need to employ a minimum number of RNs thus requiring higher RN-to-resident ratios. Likewise, as illustrated in Exhibit 28, larger states that have higher RN hours per resident day in nursing facilities tend to have lower LPN hours per resident day while smaller states tend to use more RNs and fewer LPNs (possibly suggesting some level of substitution or differences in availability of LPNs by state).

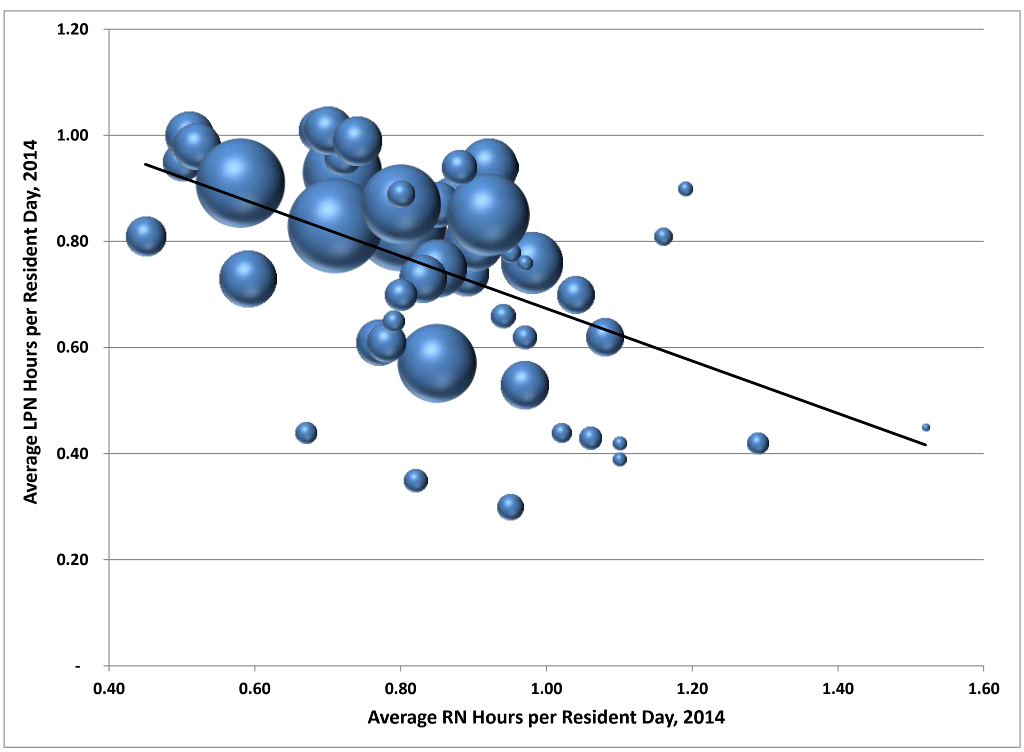
These workforce models were developed using a microsimulation approach in part with the goal to be forward looking to reflect evolving standards of care, newly enacted policies, and changing economic factors. To date, data limitations have limited the ability to model some emerging care delivery models. However, increasingly data is becoming available to model trends in care use and delivery. This research in progress is part of ongoing efforts to continue to refine and improve the microsimulation models.

Exhibit 27. State Correlation between # Nursing Facility Residents and RN Hours/Day



Note: Bubble size is based on number of nursing facility residents in state.

Exhibit 28. State Correlation between RN Hours/Day and LPN Hours/Day



Note: Bubble size is based on number of nursing facility residents in state.

VI. APPENDIX I: ADDITIONAL TABLES

Exhibit A- 1. Nursing Facility Hours per Resident Day, 2014

		Hours per Resident Day		
State	Residents	RNs	LPNs	Assistants
AK	622	1.52	0.45	3.33
AL	22,743	0.69	1.01	2.63
AR	17,596	0.50	0.95	2.78
AZ	11,118	0.94	0.94	2.49
CA	97,970	0.80	0.83	2.59
CO	16,347	1.04	0.70	2.41
CT	24,203	0.89	0.74	2.43
DC	2,523	1.19	0.90	2.85
DE	4,281	0.94	0.82	2.52
FL	73,275	0.72	0.93	2.77
GA	27,517	0.51	1.00	2.13
HI	2,221	1.10	0.39	2.67
IA	24,849	0.77	0.61	2.33
ID	3,901	1.16	0.81	2.65
IL	72,542	0.85	0.57	2.18
IN	39,028	0.92	0.94	2.26
KS	18,046	0.78	0.61	2.62
KY	23,386	0.87	0.88	2.44
LA	25,873	0.52	0.98	2.25
MA	41,044	0.90	0.80	2.38
MD	24,513	0.85	0.87	2.35
ME	6,175	1.06	0.43	2.94
MI	39,447	0.85	0.75	2.50
MN	26,616	0.83	0.73	2.41
MO	38,409	0.59	0.73	2.47
MS	16,139	0.72	0.96	2.36
MT	4,564	1.02	0.44	2.58
NC	35,969	0.75	0.85	2.39
ND	5,603	0.79	0.65	2.90
NE	12,011	0.80	0.70	2.47
NH	6,775	0.97	0.62	2.48
NJ	45,242	0.98	0.76	2.29
NM	5,453	0.67	0.44	1.95
NV	4,788	0.95	0.78	2.36
NY	105,131	0.71	0.83	2.34
OH	74,828	0.80	0.87	2.31
OK	18,938	0.45	0.81	2.51
OR	7,079	0.94	0.66	3.13
PA	79,442	0.92	0.85	2.24
RI	8,020	0.95	0.30	2.58
SC	14,697	0.88	0.94	2.44
SD	6,374	0.82	0.35	2.38
TN	27,504	0.70	1.01	2.23
TX	93,086	0.58	0.91	2.29
UT	5,522	1.29	0.42	2.64
VA	28,457	0.74	0.99	2.30
VT	2,690	0.97	0.76	2.53
WA	17,063	1.08	0.62	2.60
WI	27,171	0.97	0.53	2.57
WV	8,852	0.80	0.89	2.18
WY	2,340	1.10	0.42	2.42
US	1,347,983	0.79	0.80	2.42

Source: http://kff.org/medicaid/report/nursing-facilities-staffing-residents-and-facility-deficiencies-2009-through-2014/

Exhibit A- 2. State Population Projection Sources

State	Source
AL	IHS Population Projections Data
AK	http://labor.alaska.gov/research/pop/popproj.htm
AZ	http://azstats.gov/population-projections.aspx
AR	IHS Population Projections Data
CA	http://www.dof.ca.gov/research/demographic/reports/view.php
CO	https://dola.colorado.gov/demog_webapps/dashboard.jsf
CT	http://ctsdc.uconn.edu/projections.html
DE	http://stateplanning.delaware.gov/information/dpc_projections.shtml
DC	IHS Population Projections Data
FL	University of Florida
GA	IHS Population Projections Data
HI	http://dbedt.hawaii.gov/economic/economic-forecast/2040-long-range-forecast/
ID	IHS Population Projections Data
IL	https://data.illinois.gov/dataset/IDPH-Population-Projections-For-Illinois-By-Age-An/5m4f-swbm
IN	http://www.stats.indiana.edu/topic/projections.asp
IA	http://data.iowadatacenter.org/browse/projections.html
KS	IHS Population Projections Data
KY	http://ksdc.louisville.edu/index.php/kentucky-demographic-data/projections
LA	http://louisiana.gov/Explore/Population_Projections/
ME	http://www.maine.gov/economist/projections/index.shtml
MD	IHS Population Projections Data
MA	http://www.umass.edu/miser/population/miserproj.html
MI	http://www.michigan.gov/cgi/0,1607,7-158-54534-116118--,00.html
MN	http://www.demography.state.mn.us/resource.html?Id=33558
MS	IHS Population Projections Data
MO	http://content.oa.mo.gov/budget-planning/demographic-information/population-projections
MT	http://ceic.mt.gov/Population/PopProjections_AllCountiesPage.aspx
NE	http://www.neded.org/files/research/stathand/bsect11.htm
NV	IHS Population Projections Data
NH	http://www.nh.gov/oep/data-center/documents/2013-projections-state-counties.pdf
NJ	http://lwd.dol.state.nj.us/labor/lpa/dmograph/lfproj/lfproj_index.html
NM	IHS Population Projections Data
NY	https://pad.human.cornell.edu/index.cfm
NC	IHS Population Projections Data
ND	IHS Population Projections Data
OH	http://development.ohio.gov/reports/reports_pop_proj_map.htm
OK	http://www.okcinvestors.com/info/Oklahoma_Population_Projections.pdf
OR	IHS Population Projections Data
PA	https://pasdc.hbg.psu.edu/Data/Projections/tabid/1013/Default.aspx
RI	http://www.planning.ri.gov/documents/census/tp162.pdf
SC	S.C. Revenue and Fiscal Affairs Office
SD	http://dlr.sd.gov/lmic/menu_demographics.aspx
TN	http://tndata.utk.edu/sdcdemographics.htm
TX	http://osd.texas.gov/Data/TPEPP/Projections/
UT	IHS Population Projections Data
VT	IHS Population Projections Data
VA	http://www.coopercenter.org/demographics/virginia-population-projections
WA	http://www.ofm.wa.gov/pop/stfc/default.asp
WV	IHS Population Projections Data
WI	http://doa.wi.gov/divisions/intergovernmental-relations/demographic-services-center/projections
WY	http://eadiv.state.wy.us/pop
US	http://www.census.gov/population/projections/data/national/2014.html

Exhibit A- 3. Condition Categories for Modeling Hospitalizations and Emergency Department Visits

Primary Condition Category	ICD-9 Diagnosis Codes	ICD-9 Procedure Codes
Allergy & Immunology	477	
Cardiology	390 -459; 745 -747; 785	
Colorectal Surgery	153 -154	
Dermatology	680 -709; 757, 782	
Endocrinology	240 -279; 783	
Gastroenterology	520 -538; 555 -579; 750 -751; 787	42- 54
Infectious Diseases	001 -139	
Obstetrics & Gynecology	614 -679; V22-V24	72 -75
Hematology & Oncology	140 -239; 280 -289 ;790	
Nephrology	580 -589	55
Neurology	320 -359 ;742, 781, 784; 800 -804	
General Surgery	860 -904; 925 -939; 958 -959; 996 -999	40 -54; 30 -34)
Ophthalmology	360 -379	8 -16; 95
Orthopedic Surgery	710 -724; 730 -739; 754 -756 ; 805 -848	76-84
Otolaryngology	380 -389; 744	18-29
Perinatal/Neonatal	760-779	
Physical Medicine & Rehabilitation	840 -848 ;or 723 -724; 726 - 727; 717	93
Plastic Surgery	940 -949; 749	81
Psychiatry	290 -319	94
Pulmonology	460 -476; 478 -519; 748, 786	
Rheumatology	725 -729	
Thoracic Surgery	426, 427, 780, 785	35,36,37
Urology	590 -608; 753,788,789,791	55 -64
Neurological Surgery	850-854; 950 -958	
Vascular Surgery	440 -448	35-39

Exhibit A- 4. National APRN-to-Physician Staffing Ratios, 2013

	NPs, 2013	Physicians, 2013	Patient Demand for Services [a]	Population Total	Staffing Ratios, 2013
Nurse Practitioners					
Primary Care	70,578	249,009			
Family Medicine	40,060	98,902			0.405
General IM	13,313	97,604			0.136
Pediatrics	9,916	48,898			0.203
Geriatric Medicine	7,289	3,605			2.022
Medical Specialties	34,903	125,602			
Allergy & Immunology	1,881	4,481			0.146
Infectious Diseases	1,230	8,423			0.146
Cardiology	8,776	27,943			0.314
Dermatology	1,888	11,380			0.166
Endocrinology	2,388	7,441			0.321
Gastroenterology	2,689	14,611			0.184
Hematology & Oncology	6,980	15,889			0.439
Hospitalist	3,015		185,210,071[b]		0.000
Nephrology	1,671	9,198			0.182
Pediatric subspecialties	5,892	[c]			0.120
Perinatal/Neonatal	3,052	4,816			0.634
Critical Care/Pulmonology	1,995	15,949			0.125
Rheumatology	568	5,471			0.104
Surgery	25,204	109,739			0.082
General Surgery	2,320	28,197			0.082
Obstetrics & Gynecology	15,775	41,720			0.378
Orthopedic Surgery	2,824	25,421			0.111
Thoracic Surgery	2991	4490			0.666
Urology	1,294	9,911			0.131
Other	22,909	149,492			
Emergency Medicine	5,427	39,344			0.138
Neurology	2,271	16,104			0.141
Physical Medicine & Rehabilitation	1,189	10,841			0.110
Psychiatry	11,007	48,375			0.228
Radiology	963	34,828			0.028
Other Med Spec	2,052		667,792[d]		0.003
Urgent Care	3,674	[e]			0.037
Long Term Care	2,055			19,498,075[g]	0.000
School Health	2,983			49,487,523[h]	0.000
Nurse Anesthetists	44,660	[i]			0.972
Nurse Midwives	11,100	[j]			0.266

Notes: Clinical nurse specialists were not modeled due to data limitations. [a] Patient demand for services is defined by number of encounters to inpatient days weighted by the proportion of FTE physicians delivering care in that setting. [b,d] Workload driver is total inpatient days and inpatient days for other medical specialties. [c,e] Workload driver is total pediatrics FTE and total encounters to family medicine. [g,h] Workload driver is the population over 75 and the school age population (6-17). [i,j] Workload driver is total encounters to anesthesiologists and to obstetricians & gynecologists.

Exhibit A- 5. Staffing for Professions with Single Workload Drivers: 2012

Provider Type	Estimated Providers[1]	Estimated Visits[2]	Provider to Visit Ratio	Provider Source	Visits Source
Oral Health					
Dentists	190,800	215,700,000	1:1,130	2010 ADA	2007-11 MEPS[1]
Dental hygienists	153,600	285,200,000	1:1,860	2012 OES	2007-11 MEPS[1]
EMT/paramedic	235,463	22,700,000	1: 96	2013 ACS	2012 NIS; 2009-2010 NHAMCS

Source: [1] MEPS 2007-2011 applied to 2012 population.

Exhibit A- 6. Summary of RN/LVN Workload Drivers by Work Setting

	Distribution (%)		Number		Workload [a]		Staffing Ratios (workload per nurse)	
	RN [b]	LPN [c]	RNs	LPNs	Volume	Metric	RNs	LPNs
Office	7.4	8.6	214,344	62,776	957,824,918	Visits	4,469	15,258
Outpatient	4.0	5.7	115,862	41,607	44,293,310	Visits	382	1,065
Inpatient	55.6	29.3	1,610,476	213,876	171,483,258	Days	106	802
Emergency	6.4	0.0	185,379	--	113,437,741	Visits	612	--
Home Health Care	6.2	6.3	179,586	45,987	11,307,359	Visits	63	246
Nursing Home	5.3	30.7	153,517	224,096	19,173,536	Population 75+	125	86
Residential Care	1.7	1.3	49,241	9,489	19,173,536	Population 75+	389	2,021
School Health	1.9	--	55,034	--	49,526,495	Students	900	--
Nurse Education	3.1	0.3	89,793	2,190	150,266 (RNs) 64,061 (LPNs)	NCLEX 1st time takers	2.4 (RN+LPN)	29.3 (LPN)
All Other	8.4	17.8	243,309	129,932	314,004,465	Population	1,291	2,417
Total	100	100	2,896,540[d]	729,953[d]				

Sources: [a] estimates from HWSM; [b] BLS Occupational Employment Statistics 2012; [c] HRSA/NCHWA *The US Nursing Workforce: Trends in Supply and Education,* 2013, Table 6. Data from 2008-2010 pooled ACS; [d] ACS 2006-2012

Exhibit A- 7. Physician Assistant-to-Physician Staffing Ratios, 2014

	PAs, 2014	Physicians, 2014	PA-to-Physician Ratio, 2014
Primary Care	35,372	221,171	
Family Medicine	23,429	91,988	0.25469572
General IM	8,036	76,099	0.10559750
Pediatrics	3,530	49,831	0.07084441
Geriatric Medicine	376	3,253	0.11572367
Medical Specialties	18,563	128,927	
Allergy & Immunology	692	4,501	0.15369224
Cardiology	5,758	28,396	0.20277907
Dermatology	4,018	11,618	0.34584503
Endocrinology	440	7,734	0.05683642
Gastroenterology	1,658	14,976	0.11068394
Hematology & Oncology	2,060	16,341	0.12604554
Hospitalist	2,746	25,323	0.10844481
Nephrology	383	9,517	0.04021410
Critical Care/Pulmonology	466	16,463	0.02832934
Rheumatology	342	5,654	0.06057116
Surgery	23,621	156,343	
General Surgery	3,167	28,364	0.11166719
Neurological Surgery	2,449	5,179	0.47290169
Obstetrics & Gynecology	2,062	42,017	0.04907376
Ophthalmology	84	18,588	0.00451840
Orthopedic Surgery	11,126	25,617	0.43432873
Otolaryngology	1,079	9,466	0.11394004
Plastic Surgery	778	7,755	0.10033176
Urology	1,710	9,937	0.17205730
Vascular Surgery	1,166	3,180	0.36657321
Other	23,625	250,450	
Anesthesiology	770	46,587	0.01653148
Emergency Medicine	14,788	40,643	0.36384481
Neurology	927	16,475	0.05623799
Physical Medicine & Rehabilitation	992	11,296	0.08777537
Psychiatry	1,320	45,835	0.02880749
Radiology	881	35,249	0.02498565
Other Med Spec	3,948	29,588	0.13344666

Exhibit A- 8. Summary of Behavioral Health Profession Workload Drivers: US Total 2013

Setting:	Hospitals	Emergency Department	Outpatient	Offices	Residential Care/Nursing Home	Schools	Academia	Other
Workload Metric	**Days**	**Visits**	**Visits**	**Visits**	**Residents**	**Students**	**Graduates**	**Population**
Psychiatrists	12,309,000	4,610,000	1,523,000	26,138,000	19,498,000	49,488,000	1,575	316,439,000
Psychologists			850,000	22,994,000			5,744	
Nurse practitioners	17,509,000	3,256,000	17,459,000	956,000			683	
Physician assistants			17,449,000	809,000			71	
Addiction counselors	2,665,000	NA	2,696,000	-			4,081	
Clinical social workers			2,696,000	-			5,038	
Mental health counselors	17,509,000		17,394,000	-			2,462	
School counselors	-		-	-			5,631	
Family therapists	-		72,000	141,000			662	
Staffing Ratios (workload per provider)								
Psychiatrists	2,080	NA	210	1,120			NA	34,740
Psychologists	550	NA	70	270	10,430	3,310	0.2	15,420
Nurse practitioners	13,790	20,350	13,860	410	12,500	824,800	2.1	433,480
Physician assistants	41,690	108,530	41,550	2,310			NA	5,273,980
Addiction counselors	260	NA	180		1,270		NA	7,150
Clinical social workers	160	NA	90		1,170		NA	6,640
Mental health counselors	1,220	NA	810		900		NA	5,070
School counselors	NA	NA				200	NA	
Family therapists	NA	NA	10	10	12,740		0.2	103,070

Source: Projections for 2013 from HDMM.

Exhibit A- 9. Summary of Workload Measures and Staffing Ratios for Health Care Support and Technical Occupations

Health Workforce DISTRIBUTION (N) by Delivery Site										
		Delivery Sites								
Profession	**Total**	***Ambulatory***	***Emergency***	***Inpatient***	***Home Health***	***Nursing Home***	***Public Health***	***School Health***	***Education***	***Other***
Behavioral Health Services										
Psychologists	100% (188,300)	100% (188,300)								
Diagnostic Services										
Diagnostic medical sonographers	100% (58,000)	38% (21,771)		61% (35,616)					1% (613)	
Medical and clinical laboratory technicians	100% (161,500)	20% (32,300)	5% (8,075)	75% (121,125)						
Medical and clinical laboratory technologists	100% (164,300)	20% (32,860)	5% (8,215)	75% (123,225)						
Nuclear medicine technologists	100% (20,900)	31% (6,386)		68% (14,243)					1% (271)	
Radiologic technologists	100% (194,790)	34% (66,139)		64% (123,862)			2% (4,788)			
Dietary and Nutrition Services										
Dietitians and nutritionists	100% (67,400)	18% (12,097)		35% (23,703)	2% (1,392)	11% (7,394)	20% (13,162)	2% (1,685)		12% (7,967)
Direct Care Services										
Home health aides	100% (839,930)				100% (839,930)					
Nursing assistants	100% (1,420,020)	7% (97,350)		26% (371,080)	5% (63,490)	55% (786,660)				7% (101,440)
Pharmacy Services										
Pharmacists	100% (264,100)	78% (206,451)	22% (57,649)							
Pharmacy technicians	100% (334,400)	84% (280,730)	16% (53,670)							
Pharmacy aids	100% (42,600)	95% (40,380)	5% (2,220)							
Rehabilitation Services										

Health Workforce DISTRIBUTION (N) by Delivery Site										
Profession	**Total**	**Delivery Sites**								
		Ambulatory	***Emergency***	***Inpatient***	***Home Health***	***Nursing Home***	***Public Health***	***School Health***	***Education***	***Other***
Occupational Therapists	100% (86,286)	26% (22,780)		38% (32,444)	11% (9,319)	11% (9,319)		14% (12,425)		
Physical Therapists	100% (191,563)	46% (87,353)		34% (64,365)	12% (23,754)	8% (16,091)				
Occupational therapy assistants	100% (29,500)	46% (13,548)		18% (5,272)	6% (1,643)	24% (7,026)		7% (2,011)		
Physical therapy assistants	100% (76,492)	46% (35,309)		32% (24,164)	9% (7,160)	13% (9,860)				
Respiratory Care Services										
Respiratory therapist	100% (104,086)	19% (19,755)	44% (46,290)	37% (38,018)	0.02% (23)					
Respiratory therapy technicians	100% (13,460)	19% (2,555)	44% (5,986)	37% (4,916)	0.02% (3)					
Therapeutic Services										
Chiropractor	100% (58,800)	100% (58,800)								
Podiatrists	100% (10,700)	100% (10,700)								
Vision Services										
Optometrist	100% (36,260)	100% (36,260)								
Opticians	100% (54,500)	100% (54,500)								

Source: May 2012 Occupational Employment Statistics and HDMM baseline results

Health Workforce WORKLOAD by Care Delivery Site									
Profession	Delivery Sites (Units)								
	Ambulatory (Visits)	*Emergency (Visits)*	*Inpatient (Days)*	*Home Health (Visits)*	*Nursing Home (Population)*	*Public Health (Population)*	*School Health (Population)*	*Education (Trainees)*	*Other (Population)*
Behavioral Health Services									
Psychologists	5,726,228								
Diagnostic Services									
Diagnostic medical sonographers	957,824,918		171,483,258					Not Estimated	
Medical and clinical laboratory technicians	957,824,918	113,437,741	171,483,258						
Medical and clinical laboratory technologists	957,824,918	113,437,741	171,483,258						
Nuclear medicine technologists	3,208,056		34,404					Not Estimated	
Radiologic technologists	3,208,056		34,404			314,004,465			
Dietary and Nutrition Services									
Dietitians and nutritionists	957,824,918		171,483,258	65,361,194	19,173,536	314,004,465	58,004,764		314,004,465
Direct Care Services									
Home health aides				34,887,385					
Nursing assistants	1.002,118,228	113,437,258	171,483,258	4,477,903	19,173,536				314,004,465
Pharmacy Services (Prescriptions)									
Pharmacist	1,955,699,897	224,332,952							
Pharmacy technicians	1,955,699,897	224,332,952							
Pharmacy aids	1,955,699,897	224,332,952							
Rehabilitation Services									

Health Workforce WORKLOAD by Care Delivery Site									
Profession	Delivery Sites (Units)								
	Ambulatory (Visits)	***Emergency (Visits)***	***Inpatient (Days)***	***Home Health (Visits)***	***Nursing Home (Population)***	***Public Health (Population)***	***School Health (Population)***	***Education (Trainees)***	***Other (Population)***
Occupational Therapist	1,840,597		680,697	310,041	19,173,536		58,004,764		
Physical Therapist	60,755,485		680,697	745,589	19,173,536				
Occupational therapy assistants	1,840,597		680,697	310,041	19,173,536		58,004,764		
Physical therapy assistants	60,755,485		680,697	745,589	19,173,536				
Respiratory Care Services									
Respiratory Therapist	11,389,732	21,660,663	15,446,529	21,525					
Respiratory therapy technicians	11,389,732	21,660,663	15,446,529	21,525					
Therapeutic Services									
Chiropractor	57,275,468								
Podiatrists	12,437,351								
Vision Services									
Optometrist	24,732,085								
Opticians	24,732,085								

Source: May 2012 Occupational Employment Statistics and HDMM baseline results.

Exhibit A- 10. Summary Regression Results for RNs

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	-2.67	**	35.15	**			
Unemployment rate (state, year)	-0.15	**	0.05	*	1.03	1.01	1.05
State occupation mean hourly wage	0.85	**					
Predicted hourly wage			0.01		0.97	0.96	0.99
Age 35 to 44	3.87	**	0.26	**			
Age 45 to 54	5.21	**	1.20	**			
Age 55 to 59	5.79	**	0.88	**			
Age 60 to 64	5.74	**	-0.31	**			
Age 65 to 69	4.70	**	-4.54	**			
Age 70+	2.07	**	-8.57	**			
Age 30-34					0.69	0.63	0.77
Age 35-39					0.89	0.79	1.00
Age 40 to 44					0.97	0.86	1.08
Age 45 to 49					1.12	0.99	1.27
Male	1.18	**	2.78	**	0.71	0.58	0.87
Age 30-34 * male					2.20	1.59	3.06
Age 35-39 * male					2.81	1.96	4.02
Age 40 to 44 * male					2.63	1.87	3.70
Age 45 to 49 * male					1.94	1.38	2.74
Year 2011	-0.38	**	0.14		0.93	0.84	1.03
Year 2012	0.39	**	0.21	*	0.92	0.83	1.02
Year 2013	0.14		0.30	**	0.93	0.84	1.05
Year 2014	-0.29	**	0.38	**	0.97	0.85	1.10
Non-Hispanic black	-0.15		2.28	**	1.32	1.17	1.49
Non-Hispanic other	-0.66	**	1.43	**	1.23	1.10	1.37
Hispanic	1.12	**	1.43	**	1.38	1.19	1.60
Have nursing baccalaureate degree	2.55	**	-0.24	**	0.98	0.91	1.05
Having nursing graduate degree	4.10	**	1.56	**	0.91	0.80	1.03
Population % suburban	12.99	**	0.73		2.27	1.33	3.89
Population % rural	0.56		1.41	**	0.77	0.52	1.15
Sample size	150,504		150,504				89,370
R-squared	0.12		0.04				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50.

Exhibit A- 11. Summary Regression Results for LPNs

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	-0.46		34.44	**			
Unemployment rate (state, year)	-0.03		0.05		0.99	0.96	1.03
State occupation mean hourly wage	0.84	**					
Predicted hourly wage			0.04		1.01	0.99	1.04
Age 35 to 44	2.15	**	1.85	**			
Age 45 to 54	2.80	**	2.04	**			
Age 55 to 59	3.41	**	1.52	**			
Age 60 to 64	3.43	**	0.35				
Age 65 to 69	3.42	**	-4.33	**			
Age 70+	2.58	**	-7.42	**			
Age 30-34					1.00	0.87	1.16
Age 35-39					1.08	0.92	1.26
Age 40 to 44					1.10	0.94	1.29
Age 45 to 49					1.08	0.92	1.27
Male	0.62	**	1.77	**	1.39	1.03	1.88
Age 30-34 * male					1.36	0.77	2.41
Age 35-39 * male					1.06	0.62	1.81
Age 40 to 44 * male					1.31	0.76	2.27
Age 45 to 49 * male					0.79	0.48	1.29
Year 2011	-0.46	**	-0.02		0.89	0.76	1.04
Year 2012	-0.44	**	0.27		0.87	0.74	1.02
Year 2013	-0.40	**	0.17		0.91	0.76	1.08
Year 2014	-1.72	**	0.22		0.80	0.66	0.98
Non-Hispanic black	0.60	**	1.05	**	1.42	1.24	1.62
Non-Hispanic other	0.38	*	1.16	**	0.91	0.77	1.09
Hispanic	-0.82	**	1.04	**	1.04	0.88	1.22
Population % suburban	7.57	**	-2.09	*	1.26	0.54	2.95
Population % rural	1.43	**	1.96	**	0.47	0.26	0.84
Sample size	37,294		37,294				23,348
R-squared	0.11		0.04				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50.

Exhibit A- 12. Summary Regression Results for Dental Hygienists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	3.48	**	33.15	**			
Unemployment rate (state, year)	-0.20	**	-0.06		0.97	0.90	1.05
State occupation mean hourly wage	0.76	**					
Predicted hourly wage			-0.06	*	0.98	0.95	1.01
Age 35 to 44	2.65	**	-1.49	**			
Age 45 to 54	2.87	**	-1.36	**			
Age 55 to 59	3.09	**	-2.34	**			
Age 60 to 64	2.71	**	-3.06	**			
Age 65 to 69	1.47	*	-4.62	**			
Age 70+	0.62		-8.79	**			
Age 30-34					0.78	0.58	1.06
Age 35-39					1.09	0.78	1.51
Age 40 to 44					1.49	1.05	2.10
Age 45 to 49					1.39	0.99	1.96
Male	-2.29	**	5.53	**	0.44	0.20	0.97
Age 30-34 * male					2.40	0.57	10.20
Age 35-39 * male					5.04	0.58	43.74
Age 40 to 44 * male					NA		
Age 45 to 49 * male					NA		
Year 2011	-0.33		0.08		1.08	0.77	1.52
Year 2012	-1.32	**	0.27		0.80	0.56	1.13
Year 2013	-1.15	**	0.01		0.85	0.58	1.23
Year 2014	-0.76		0.58		1.07	0.69	1.66
Non-Hispanic black	-1.01		5.02	**	0.76	0.41	1.40
Non-Hispanic other	-0.10		1.17	*	0.57	0.40	0.80
Hispanic	-1.75	**	2.36	**	0.97	0.66	1.45
Population % suburban	10.07	**	7.24	**	4.73	0.83	27.05
Population % rural	3.22	*	-1.69		4.99	0.94	26.38
Sample size	8,608		8,608				6,166
R-squared	0.16		0.04				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.

Exhibit A- 13. Summary Regression Results for Physical Therapists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	-0.46		33.57	**			
Unemployment rate (state, year)	0.05		0.06		1.09	1.00	1.18
State occupation mean hourly wage	0.72	**					
Predicted hourly wage			0.11	**	0.99	0.97	1.02
Age 35 to 44	4.47	**	-2.70	**			
Age 45 to 54	4.30	**	-1.56	**			
Age 55 to 59	3.27	**	-1.14	**			
Age 60 to 64	2.77	**	-1.92	**			
Age 65 to 69	2.13	*	-5.96	**			
Age 70+	0.19		-10.25	**			
Age 30-34					1.20	0.84	1.72
Age 35-39					0.79	0.56	1.11
Age 40 to 44					1.12	0.78	1.61
Age 45 to 49					1.66	1.09	2.53
Male	1.97	**	6.50	**	1.01	0.63	1.60
Age 30-34 * male					2.46	1.08	5.60
Age 35-39 * male					8.29	2.99	22.97
Age 40 to 44 * male					29.17	3.83	222.49
Age 45 to 49 * male					7.13	1.59	32.04
Year 2011	0.08		-0.42		1.00	0.71	1.41
Year 2012	0.29		-0.42		1.12	0.78	1.61
Year 2013	0.28		-0.38		1.00	0.69	1.44
Year 2014	0.28		0.03		1.54	0.99	2.40
Non-Hispanic black	-1.04		1.24	*	1.15	0.58	2.28
Non-Hispanic other	0.79	*	0.74	*	0.81	0.59	1.10
Hispanic	-2.95	**	1.26	*	0.45	0.30	0.67
Population % suburban	10.78	**	-1.75		4.11	0.50	34.07
Population % rural	3.14	*	-1.16		0.81	0.19	3.44
Sample size	10,771		10,771				8,249
R-squared	0.19		0.1				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50.

Exhibit A- 14. Summary Regression Results for Pharmacists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	-3.36	*	33.23	**			
Unemployment rate (state, year)	-0.20		-0.03		1.08	1.00	1.16
State occupation mean hourly wage	0.91	**					
Predicted hourly wage			0.06	**	0.98	0.96	1.00
Age 35 to 44	8.73	**	1.13	**			
Age 45 to 54	8.84	**	1.80	**			
Age 55 to 59	8.61	**	1.89	**			
Age 60 to 64	7.83	**	0.20				
Age 65 to 69	4.97	**	-4.38	**			
Age 70+	1.51	*	-10.62	**			
Age 30-34					1.97	1.44	2.69
Age 35-39					1.67	1.19	2.33
Age 40 to 44					2.91	1.96	4.33
Age 45 to 49					3.63	2.31	5.70
Male	1.87	**	3.79	**	1.32	0.97	1.79
Age 30-34 * male					2.17	1.05	4.45
Age 35-39 * male					3.52	1.69	7.35
Age 40 to 44 * male					1.72	0.80	3.69
Age 45 to 49 * male					1.71	0.73	4.01
Year 2011	-0.52		0.36		1.28	0.94	1.74
Year 2012	-1.30	**	0.30		1.20	0.89	1.64
Year 2013	-1.38	**	0.73	*	1.62	1.15	2.26
Year 2014	-2.29	**	0.48		1.86	1.25	2.75
Non-Hispanic black	-3.92	**	1.20	**	1.19	0.72	1.97
Non-Hispanic other	-1.59	**	0.51	*	0.75	0.59	0.96
Hispanic	-3.90	**	0.25		0.72	0.46	1.12
Population % suburban	-4.80		-6.97	**	1.36	0.19	9.69
Population % rural	-4.22	*	2.05		2.53	0.63	10.20
Sample size	14,488		14,488				9,556
R-squared	0.2		0.08				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50.

Exhibit A- 15. Summary Regression Results for Occupational Therapists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	3.06	*	32.65	**			
Unemployment rate (state, year)	-0.01		0.00		1.00	0.89	1.13
State occupation mean hourly wage	0.70	**					
Predicted hourly wage			0.14	**	0.94	0.91	0.98
Age 35 to 44	2.22	**	-2.72	**			
Age 45 to 54	2.64	**	-1.76	**			
Age 55 to 59	2.03	**	-0.98	*			
Age 60 to 64	2.39	**	-2.74	**			
Age 65 to 69	0.22		-5.54	**			
Age 70+	0.32		-13.60	**			
Age 30-34					0.55	0.31	0.97
Age 35-39					0.35	0.21	0.58
Age 40 to 44					0.49	0.28	0.84
Age 45 to 49					1.08	0.55	2.09
Male	1.35	**	5.97	**	1.62	0.21	12.31
Age 30-34 * male					NA		
Age 35-39 * male					2.45	0.21	29.29
Age 40 to 44 * male					3.31	0.19	57.09
Age 45 to 49 * male					NA		
Year 2011	0.22		0.07		0.71	0.43	1.19
Year 2012	-0.11		0.82		0.82	0.47	1.42
Year 2013	-0.11		0.22		0.63	0.36	1.10
Year 2014	-0.41		0.54		0.83	0.43	1.59
Non-Hispanic black	0.53		3.01	**	1.74	0.63	4.82
Non-Hispanic other	1.34	*	1.04		1.16	0.65	2.08
Hispanic	-2.34	**	0.43		1.09	0.50	2.40
Population % suburban	7.81	**	-2.99		17.33	0.98	307.60
Population % rural	2.36		-0.66		0.53	0.08	3.56
Sample size	4,989		4,989				3,779
R-squared	0.18		0.07				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.

Exhibit A- 16. Summary Regression Results for Dietitians

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	6.22	**	34.01	**			
Unemployment rate (state, year)	-0.12		-0.23		1.08	0.99	1.19
State occupation mean hourly wage	0.56	**					
Predicted hourly wage			0.18		0.92	0.84	1.00
Age 35 to 44	3.14	**	-1.43	*			
Age 45 to 54	2.32	**	-0.24				
Age 55 to 59	3.00	**	0.58				
Age 60 to 64	1.49	**	-0.97				
Age 65 to 69	1.77	*	-3.27	**			
Age 70+	0.13		-8.91	**			
Age 30-34					0.72	0.49	1.04
Age 35-39					0.89	0.56	1.42
Age 40 to 44					1.27	0.78	2.08
Age 45 to 49					1.33	0.84	2.10
Male	-0.20		5.10	**	0.63	0.32	1.23
Age 30-34 * male					NA		
Age 35-39 * male					2.71	0.68	10.80
Age 40 to 44 * male					5.92	0.71	49.38
Age 45 to 49 * male					1.60	0.45	5.65
Year 2011	0.65		0.09		1.13	0.75	1.71
Year 2012	0.24		0.04		0.96	0.64	1.44
Year 2013	-0.22		0.17		1.64	1.02	2.62
Year 2014	-0.33		-0.42		1.15	0.69	1.90
Non-Hispanic black	-4.04	**	2.89	**	0.84	0.48	1.46
Non-Hispanic other	-0.70		1.94	**	0.66	0.43	1.00
Hispanic	-3.70	**	1.39		0.81	0.46	1.40
Population % suburban	6.88	**	-0.83		3.83	0.38	38.72
Population % rural	-4.21	*	-0.02		1.11	0.19	6.55
Sample size	4,641		4,641				3,016
R-squared	0.07		0.05				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.

Exhibit A- 17. Summary Regression Results for Optometrists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	5.14		37.97	**			
Unemployment rate (state, year)	0.14		-0.06		0.84	0.57	1.24
State occupation mean hourly wage	0.45	**					
Predicted hourly wage			-0.03		0.99	0.87	1.13
Age 35 to 44	4.98	**	-0.74				
Age 45 to 54	3.24	*	0.18				
Age 55 to 59	-2.25		0.37				
Age 60 to 64	0.02		-2.50	**			
Age 65 to 69	-3.68		-6.03	**			
Age 70+	-6.04	*	-14.19	**			
Age 30-34					NA		
Age 35-39					1.54	0.19	12.46
Age 40 to 44					0.39	0.07	2.26
Age 45 to 49					0.25	0.05	1.29
Male	3.84	**	5.40	**	NA		
Age 30-34 * male					NA		
Age 35-39 * male					NA		
Age 40 to 44 * male					NA		
Age 45 to 49 * male					NA		
Year 2011	1.54		-0.42		0.66	0.15	2.85
Year 2012	5.34	**	0.75		0.88	0.17	4.59
Year 2013	4.98	**	0.58		1.38	0.22	8.53
Year 2014	4.72	*	0.15		1.47	0.15	14.97
Non-Hispanic black	-7.21		3.99	*	NA		
Non-Hispanic other	-2.02		-0.40		0.41	0.13	1.33
Hispanic	4.11		2.14		NA		
Population % suburban	39.50	**	-1.38		NA		
Population % rural	8.92		4.57		NA		
Sample size	1,944		1,944				1,098
R-squared	0.12		0.13				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.

Exhibit A- 18. Summary Regression Results for Respiratory Therapists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	-2.99		35.34	**			
Unemployment rate (state, year)	-0.11		0.02		0.91	0.80	1.03
State occupation mean hourly wage	1.02	**					
Predicted hourly wage			0.00		1.01	0.92	1.10
Age 35 to 44	2.67	**	0.67				
Age 45 to 54	4.42	**	1.47	**			
Age 55 to 59	4.91	**	0.85				
Age 60 to 64	4.77	**	0.18				
Age 65 to 69	3.79	**	-4.67	**			
Age 70+	3.96	**	-4.22	**			
Age 30-34					0.54	0.28	1.03
Age 35-39					0.42	0.22	0.83
Age 40 to 44					0.55	0.28	1.10
Age 45 to 49					0.64	0.30	1.36
Male	1.80	**	2.71	**	0.75	0.28	1.97
Age 30-34 * male					12.36	1.33	114.76
Age 35-39 * male					2.57	0.69	9.60
Age 40 to 44 * male					4.22	1.00	17.79
Age 45 to 49 * male					3.28	0.83	12.97
Year 2011	-0.20		-0.12		1.38	0.78	2.46
Year 2012	-0.08		0.11		1.15	0.64	2.06
Year 2013	-0.46		0.39		0.93	0.50	1.71
Year 2014	-0.85	*	0.67		0.79	0.39	1.61
Non-Hispanic black	0.19		1.87	**	1.59	0.82	3.09
Non-Hispanic other	0.32		0.53		1.69	0.85	3.38
Hispanic	0.13		1.22	*	1.62	0.77	3.45
Population % suburban	6.14	**	-2.70		20.12	0.88	460.91
Population % rural	0.43		3.53	*	0.22	0.03	1.51
Sample size	5,560		5,560				3,494
R-squared	0.14		0.04				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50.

Exhibit A- 19. Summary Regression Results for Radiation Therapists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	-1.99		31.01	**			
Unemployment rate (state, year)	-0.15		-0.09		0.98	0.67	1.43
State occupation mean hourly wage	0.89	**					
Predicted hourly wage			0.26	**	0.86	0.73	1.00
Age 35 to 44	5.44	**	0.55				
Age 45 to 54	7.27	**	-0.45				
Age 55 to 59	5.75	**	1.03				
Age 60 to 64	6.02	**	-0.78				
Age 65 to 69	6.15	*	-3.55				
Age 70+	-2.42		-9.19	**			
Age 30-34					0.21	0.04	1.08
Age 35-39					0.69	0.09	5.11
Age 40 to 44					0.96	0.12	7.54
Age 45 to 49					7.10	0.42	119.49
Male	1.34		1.64	*	0.54	0.06	4.73
Age 30-34 * male					2.86	0.21	38.49
Age 35-39 * male					NA		
Age 40 to 44 * male					NA		
Age 45 to 49 * male					NA		
Year 2011	-0.47		-1.02		3.00	0.30	30.22
Year 2012	0.98		-1.55		0.55	0.14	2.25
Year 2013	-2.00		-1.95		0.74	0.14	3.93
Year 2014	-0.50		-1.53		0.97	0.13	7.25
Non-Hispanic black	-3.43	*	3.20	*	0.26	0.03	2.56
Non-Hispanic other	-2.59		4.78	**	0.07	0.02	0.28
Hispanic	-3.96	**	1.41		0.49	0.05	4.62
Population % suburban	2.42		4.59		NA		
Population % rural	3.01		-7.86		NA		
Sample size	805		805				583
R-squared	0.24		0.07				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.

Exhibit A- 20. Summary Regression Results for Podiatrists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]
Intercept	-22.71		41.09	**	NA
Unemployment rate (state, year)	1.66		0.33		NA
State occupation mean hourly wage	0.48	**			NA
Predicted hourly wage			-0.01		NA
Age 35 to 44	15.52	**	-4.96		
Age 45 to 54	7.47		-7.36	**	
Age 55 to 59	11.11		-7.33	**	
Age 60 to 64	6.91		-10.04	**	
Age 65 to 69	3.63		-15.96	**	
Age 70+	-13.14		-22.57	**	
Age 30-34					NA
Age 35-39					NA
Age 40 to 44					NA
Age 45 to 49					NA
Male	7.34		6.91	**	NA
Age 30-34 * male					NA
Age 35-39 * male					NA
Age 40 to 44 * male					NA
Age 45 to 49 * male					NA
Year 2011	-2.85		-0.25		NA
Year 2012	2.54		0.75		NA
Year 2013	6.64		2.55		NA
Year 2014	13.57	*	3.01		NA
Non-Hispanic black	-4.02		-5.54		NA
Non-Hispanic other	4.97		-3.13		NA
Hispanic	-12.64		5.77		NA
Population % suburban	-15.20		6.36		NA
Population % rural	47.26	*	7.29		NA
Sample size	473		473		228
R-squared	0.11		0.15		

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.

Exhibit A- 211. Summary Regression Results for Audiologists

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	15.44	**	30.67	**			
Unemployment rate (state, year)	0.21		-0.30		0.92	0.69	1.22
State occupation mean hourly wage	0.31	**					
Predicted hourly wage			0.36		1.11	0.83	1.48
Age 35 to 44	6.43	**	-4.40	*			
Age 45 to 54	4.94	**	-3.33	*			
Age 55 to 59	6.08	**	-0.73				
Age 60 to 64	3.48	*	-1.97				
Age 65 to 69	0.69		-8.36	**			
Age 70+	-2.85		-6.38				
Age 30-34					1.05	0.24	4.73
Age 35-39					0.27	0.03	2.71
Age 40 to 44					0.23	0.02	2.33
Age 45 to 49					0.98	0.11	8.32
Male	-2.61	*	7.12	**	NA		
Age 30-34 * male					NA		
Age 35-39 * male					NA		
Age 40 to 44 * male					NA		
Age 45 to 49 * male					NA		
Year 2011	-0.69		-1.03		3.04	0.78	11.90
Year 2012	-1.03		-1.38		2.47	0.59	10.41
Year 2013	-1.34		-0.08		2.20	0.54	8.91
Year 2014	-0.62		-0.54		1.96	0.43	9.02
Non-Hispanic black	-1.22		-0.35		NA		
Non-Hispanic other	-3.64		-1.74		0.19	0.03	1.06
Hispanic	-0.05		-1.76		0.34	0.09	1.29
Population % suburban	13.23		0.80		NA		
Population % rural	5.75		-10.09		NA		
Sample size	805		805				524
R-squared	0.09		0.08				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.

Exhibit A- 22. Summary Regression Results for Opticians

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	-1.52		34.38	**			
Unemployment rate (state, year)	0.12		-0.10		0.97	0.85	1.10
State occupation mean hourly wage	0.84	**					
Predicted hourly wage			0.14		1.14	1.03	1.27
Age 35 to 44	3.36	**	1.12				
Age 45 to 54	3.24	**	1.39	*			
Age 55 to 59	2.85	**	1.42	*			
Age 60 to 64	3.34	**	-0.30				
Age 65 to 69	4.31	**	-5.06	**			
Age 70+	2.86	**	-7.43	**			
Age 30-34					1.22	0.74	1.99
Age 35-39					0.89	0.47	1.70
Age 40 to 44					1.45	0.72	2.92
Age 45 to 49					2.01	0.95	4.28
Male	1.70	**	2.74	**	0.82	0.41	1.63
Age 30-34 * male					1.80	0.54	5.98
Age 35-39 * male					1.42	0.42	4.82
Age 40 to 44 * male					0.99	0.26	3.74
Age 45 to 49 * male					1.35	0.32	5.80
Year 2011	-0.08		0.56		1.15	0.63	2.07
Year 2012	0.66		-0.19		0.74	0.41	1.34
Year 2013	0.20		-0.31		0.71	0.38	1.33
Year 2014	0.91		-0.32		0.77	0.37	1.59
Non-Hispanic black	0.49		0.44		0.79	0.40	1.57
Non-Hispanic other	0.85		-0.73		0.94	0.51	1.71
Hispanic	-0.57		0.70		1.05	0.65	1.69
Population % suburban	3.59		-5.20		11.53	0.49	269.17
Population % rural	5.94	**	3.25		0.49	0.05	4.60
Sample size	2,711		2,711				1,686
R-squared	0.13		0.07				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50.

Exhibit A- 23. Summary Regression Results for Chiropractors

Parameter	Predicting Hourly Wage [a]		Predicting Hours/Week [a]		Predicting Labor Force Participation, age <50 (CI) [b]		
Intercept	17.52	**	37.00	**			
Unemployment rate (state, year)	-0.40		-0.43	*	0.85	0.66	1.09
State occupation mean hourly wage	0.22	**					
Predicted hourly wage			0.20		1.15	0.96	1.39
Age 35 to 44	5.27	**	-1.70				
Age 45 to 54	3.00	**	-2.38	**			
Age 55 to 59	2.22		-2.71	**			
Age 60 to 64	0.62		-5.94	**			
Age 65 to 69	-3.72	*	-8.89	**			
Age 70+	0.09		-12.02	**			
Age 30-34					1.12	0.29	4.33
Age 35-39					0.22	0.05	1.03
Age 40 to 44					0.29	0.06	1.41
Age 45 to 49					0.30	0.08	1.14
Male	3.64	**	3.95	**	3.06	0.30	31.21
Age 30-34 * male					0.76	0.05	12.08
Age 35-39 * male					0.95	0.08	11.46
Age 40 to 44 * male					NA		
Age 45 to 49 * male					0.67	0.06	7.73
Year 2011	-0.27		-0.19		1.33	0.49	3.66
Year 2012	-1.43		0.11		1.35	0.46	3.97
Year 2013	0.10		-0.73		0.97	0.30	3.14
Year 2014	-1.25		-0.50		0.47	0.13	1.67
Non-Hispanic black	5.86	*	-4.31	*	NA		
Non-Hispanic other	-3.90	**	0.85		1.02	0.31	3.37
Hispanic	1.37		0.07		0.33	0.11	1.06
Population % suburban	31.43	**	-4.31		NA		
Population % rural	-0.66		-0.48		3.10	0.01	926.58
Sample size	2,796		2,796				1,723
R-squared	0.07		0.08				

Notes: [a] Ordinary least squares regression coefficients. Statistically significant at the 0.01 (**) or 0.05 (*) level. [b] Odds ratios and 95% confidence interval (CI) from logistic regression. Comparison groups are female, year=2010, non-Hispanic white, age <35 (for wages and hours) or age <30 (for labor force participation). Labor force participation regression uses only clinicians under age 50. NA=estimates not available because of small sample.