Supplementary Online Content

Dieleman JL, Squires E, Bui AL, et al. Factors associated with increases in US health care spending, 1996-2013. *JAMA*.
doi:10.1001/jama.2017.15927

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This supplementary material has been provided by the authors to give readers additional information about their work.

Factors associated with increases in US health care spending, 1996–2013

Outline

1. Data sources
2. Merging data sources
3. Decomposition
4. Code
5. Results

***Note**: A substantial portion of the Section 1A in this supplement was drawn from the supplementary appendix associated with Dieleman et al.*[1]

Section 1: Data sources

Two data sources were used for this study. Health spending data came from the Disease Expenditure 2013 Project, produced by the Institute for Health Metrics and Evaluation. Epidemiologic data came from the Global Burden of Disease 2015 study.

Section 1A: Disease Expenditure data

The objective of this research was to comprehensively measure and describe spending on pediatric health care in the United States using granular, politically and clinically useful categories. We produced annual estimates for 1996 through 2013. These estimates were created to be as comprehensive as possible, and they aggregate to reflect the official US government estimates of US health spending, as reported in the National Health Expenditure Accounts (NHEA).[2] These estimates were produced to reflect actual spending on health, also known as expenditure or payments, rather than charges made by medical providers. In many cases, charges are not paid in full and tracking these would be an overestimate of the resources actually spent on health care.[3–5] Spending estimates were adjusted for inflation using the economy-wide consumer price index from the International Monetary Fund, and were reported in 2015 dollars.[6] In addition to health spending, volume of health goods or services was also estimated – measured as the number of visits, bed-days, or prescriptions filled.

This research focused on personal health care spending. Personal health care spending is defined in the NHEA as "the total amount spent to treat individuals with specific medical conditions," and in 2013 was 84.8% of total US health spending. For this study, personal health care spending was disaggregated into six types of care, including inpatient care, ambulatory care, retail pharmaceuticals, emergency department care, nursing facilities care, and dental care.

The overarching research strategy was to use microdata to inform spending and volume estimates at the most granular level possible. For the disaggregation of personal health care spending, microdata consisted of administrative records, insurance claims, or household surveys that report health spending by cause of illness or reason for the health care event, type of good or service, and demographic information. These sources provided data at the patient, encounter, or claim level. In most cases,

spending and volume estimates were disaggregated into age-, sex-, cause -, type-of-care-, and year-specific categories. Table 1 lists all sources of microdata used in the estimation process by type of care.

Table 1. Primary data sources used in DEX study

Type of care	Macro spending data and years	Micro spending data and years	Micro volume data and years
Ambulatory	NHEA (1996 – 2013)*	MEPS (1996 – 2013); SAMHSA (1998, 2002, 2004, 2005, 2009); MarketScan (2000, 2010, 2012)	NAMCS (1996 – 2011); NHAMCS (1996 – 2011); MarketScan (2000, 2010, 2012)
Inpatient	NHEA (1996 – 2013)	NIS (1996 – 2012); MEPS (1996 – 2013), SAMHSA (1998, 2002, 2004, 2005, 2009); MarketScan (2000, 2010, 2012)	NIS (1996 – 2012); MarketScan (2000, 2010, 2012)
Emergency Department	NHEA (1996 – 2013)*	MEPS (1996 – 2013); MarketScan (2000, 2010, 2012)	NHAMCS (1996 – 2011); MarketScan (2000, 2010, 2012)
Nursing care	NHEA (1996 – 2013)	Medicare claims data (1999 – 2001, 2002, 2004, 2006, 2008, 2010, 2012); NNHS (1997, 1999, 2004); MCBS (1999 – 2011); MarketScan (2000, 2010, 2012), MCBS (1999 – 2011)	Medicare claims data (1999 – 2001, 2002, 2004, 2006, 2008, 2010, 2012); NNHS (1997, 1999, 2004); MCBS (1999 – 2011); MarketScan (2000, 2010, 2012)
Dental	NHEA (1996 – 2013)	MEPS (1996 – 2013)	MEPS (1996 – 2013)
Prescribed retail pharmaceuticals	NHEA (1996 – 2013)	MEPS (1996 – 2013)	MEPS (1996 – 2013)
Other	NHEA (1996 – 2013)	Not disaggregated	Not disaggregated

To provide a comprehensive yet granular set of health spending estimates, health spending was split into categories defined by simultaneously applying three distinct frameworks. These three frameworks reflect demography, epidemiology, and the type of health care provided.

1. **Demography:** Health spending and volume of goods and services were estimated for **both sexes** and for **18 age groups**, under 1, 1-4, 5-9, 10-14, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, and 80 plus.
2. **Epidemiology:** Health spending and volume of goods and services were estimated for **155 causes**. The cause list for this project was based on the Global Burden of Disease (GBD) 2013 study.[7] GBD 2013 classified causes of health burden at five different levels of disaggregation.

Level III classification was extracted from GBD 2013 for this study. This included 144 causes of health burden. In addition to these, 14 other categories were added. Four risk factors for other underlying health causes were added because it was clear that there is substantial spending on the treatment of these risk factors, and this spending is intended to prevent a wide set of causes of illness. These additional categories are spending on the treatment of hypertension, treatment of hyperlipidemia, treatment of obesity, and tobacco cessation. Spending on these risk factors excludes health care spending on diseases caused by these risk factors but includes the cost of treating the risk factor. In addition to these, seven causes were added that were not associated with health burden (and are therefore not considered by GBD) but were associated with health spending. Examples of these causes were well-person care, pregnancy and postpartum care, and well-dental care. Finally, this project also tracked spending on three impairments. These impairments – heart failure, septicemia, and renal failure – are not underlying causes of health burden, but rather consequences of other underlying causes. Spending on these causes was tracked because they represent large portions of health spending and are of political interest. A description and full list of causes and how they map to the International Classification of Diseases version 9 (ICD-9) are provided in section three of this appendix.

3. **Types of goods or services:** Health care spending and volume of goods and services were estimated for **six types of goods and services**: ambulatory care, inpatient care, emergency department care, nursing care, dental care, and prescribed retail pharmaceuticals. Definitions for these types of goods and services were designed to reflect the underlying microdata.
    - *Ambulatory care*: Ambulatory care included preventive, curative, and rehabilitative medical and psychiatric services, procedures, and medications provided in ambulatory care settings including physicians' offices, freestanding clinics, and hospital outpatient departments. Emergency room visits and dental visits are excluded from ambulatory care. For ambulatory care, volume was measured as the number of visits.
    - *Inpatient care*: Inpatient care included all spending in an inpatient hospital facility, whether preventive, curative, or rehabilitative, and included all medical goods, whether pharmaceuticals, diagnostics, or devices, consumed by inpatients, regardless of their length of stay. Emergency room visits that result in an inpatient stay are considered inpatient care. For inpatient care, volume was measured as the number of days spent in an inpatient setting.
    - *Emergency department care*: Emergency department care included preventive, curative, and rehabilitative medical and psychiatric care provided at hospital-based and freestanding emergency departments. Emergency department care excluded visits that resulted in inpatient admission. For emergency department care, volume was measured as the number of visits.
    - *Nursing facilities care*: Nursing care included nursing care provided in nursing homes or other residential institutions. Home-based care and palliative or hospice care provided in inpatient settings were excluded. Spending on hoteling costs, such as room and board, are included. For nursing care, volume was measured as the number of days spent in a facility.

- *Dental care*: Dental care included preventive and curative health care at a dental facility. For dental care, volume was measured as the number of visits to a dental facility.
- *Prescribed retail pharmaceuticals:* Prescribed retail pharmaceuticals (pharma) included all prescription medicines purchased in a retail pharmacy setting. This category excluded any medications consumed in inpatient, ambulatory, long-term, and emergency settings during a visit. It also excluded over-the-counter (non-prescribed) medications and therapeutic devices. For prescribed retail pharmaceutical, volume was measured as the number of prescriptions filled. The cause of illness is captured by the diagnoses reported by an individual who held the prescription, not by an Anatomical Therapeutic Chemical (ATC) classification system or medication code.

For all estimates, uncertainty was propagated using a bootstrapping method.

Statistical models were used when necessary to generate a complete set of estimates, combine data sources, and adjust the data for known biases. The population-weighted estimates derived from the microestimates were compared and scaled to reflect the total health expenditure for each type of care and year. A brief summary of each step, including the types of care impacted, the effect of the process, and the motivating purpose of the process are described in Table 2 below. This table does not attempt to explain how each step was conducted. Rather, this table explains briefly why each step was conducted and how it impacted the data.

Table 2 Summary of steps taken to get final estimates

Step	Types of care	Motivation	Effect
Format data	Ambulatory, inpatient, emergency department, nursing care, dental, prescribed retail pharmaceuticals	To enable all data sources to go through same statistical machinery	All data were structured in the same manner, and variable names and variable formats were systematized across all data sources used
Bootstrap	Ambulatory, inpatient, emergency department, nursing care, dental, prescribed retail pharmaceuticals	To obtain 1,000 bootstrap samples upon which all other steps could be run independently, in order to quantify uncertainty	1,000 samples were created for analysis based on survey-adjusted bootstrapping methods
De-truncation	Ambulatory (spending data only), emergency department (spending data only), prescribed retail pharmaceuticals	To estimate more detailed four- and five-digit ICD-9 diagnoses from the three-digit diagnoses recorded in Medical Expenditure Panel Survey (MEPS)	Variation within each bootstrap draw and across draws for data from MEPS was increased
Redistribution	Ambulatory, inpatient, emergency department, nursing care, prescribed retail pharmaceuticals	To attribute all spending and volumes to causes that represent the true underlying reason for a health care encounter	Spending and volume originally attributed to ICD-9 codes that do not map to GBD causes were assigned to GBD causes based on redistribution packages developed by the IHME GBD research. This redistributions was designed to take into account age and sex. While each cause is impacted differently by the redistribution process, spending per cause, measured at the age, sex, type, and year level, goes up or stays the same, while spending attributed to “garbage codes” is removed

Mapping	Ambulatory, inpatient, emergency department, nursing care, dental, prescribed retail pharmaceuticals	To divide spending into 158 medically important and policy-relevant categories	Causes were aggregated from ICD-9 codes to 158 GBD causes, leading to more data for each cause-, year-, age-, sex-, type-combination
Injury adjustment	Ambulatory, inpatient, emergency department, nursing care, prescribed retail pharmaceuticals	To have all spending and volume due to injuries be defined by external cause of injury codes, rather than less actionable nature of injury codes	All spending attributed to injuries was defined by the external cause of injury
Comorbidity adjustment	Ambulatory, inpatient, emergency department, nursing care	To redistribute resources toward the underlying cause of the health care spending, rather than merely the primary diagnosis	Spending was moved from some causes to others, based on whether, on average, the cause leads to excess spending (as comorbidity) or is a primary diagnosis that has spending increased by excess spending on comorbidities
Age-splitting	Nursing care	To have Medicare nursing care claims data be consistent with all other data sources, as Medicare aggregates younger ages to ensure patient privacy	Charges captured in Medicare claims were split up from larger age bins into the age bins used in the study
Inpatient charges-to-payments adjustment	Inpatient	To estimate total inpatient spending from the inpatient facility charges report in the National Inpatient Sample	Inpatient spending estimates were made smaller than originally reported in National Inpatient Sample, based on cause, year, payer-specific payment to charge ratios

Completing the series	Ambulatory, inpatient, emergency department, nursing care, dental, prescribed retail pharmaceuticals	To have estimates for years in which data do not exist, to obtain estimates for spending that are missed due to survey designs, and to have estimates that are appropriately consistent across age and time	Multiple data sources were combined to leverage strengths across data sources, such that every type-, age-, year-, cause-, and sex-combination was estimated and "smooth" series were produced
Nursing-care adjustment	Nursing care	To estimate nationally representative spending and volume estimates for short- and long-term stays at nursing homes	Three data sources were leveraged together, two using linear regression, to create nationally representative spending and volume estimates for short-term and long-term nursing facility care
Mental health adjustment	Ambulatory, inpatient	To address the undersampling of mental health and substance abuse specialty facilities and create mental health and substance abuse health care spending aggregates that are commensurate with official US government estimates	Spending and volume on mental illnesses were increased, relative to non-mental illness causes, for the ambulatory and inpatient types of care
Scaling	Ambulatory, inpatient, emergency department, nursing care, dental, prescribed retail pharmaceuticals	To match spending estimates that reflect the official US government numbers, as no data source offers complete census of health care spending	Estimates for spending were increased or decreased depending on type of care

Section 1B: Global Burden of Disease data

The Global Burden of Disease study contains comprehensive estimates for disease burden for every country of the world. It contains information about mortality for 249 causes of death, information about incidence, prevalence, and years lived with disability for 310 health conditions and injuries, and information about 79 risk factors. Estimates are made at global, national, and subnational levels, in some cases. GBD contains estimates for years 1990, 2000, 2005, 2010, and 2015. For this study, we used prevalence and incidence data, as well as population data estimated in the GBD study. We extracted prevalence and incidence data for the 155 health conditions estimated by the DEX study for the United States for all years within our study period (2000, 2005, and 2010). Detailed methods for the GBD study are described elsewhere.[8]

Section 2: Merging data sources

Three steps were taken in order to merge GBD data with Disease Expenditure data. First, a single epidemiologic metric, either prevalence or incidence, was selected for conditions included in the GBD based on expert opinion. Second, various methods were used to obtain disease burden estimates for those conditions included in the DEX study but excluded from GBD because they are not considered sources of disease burden. Third, data were adjusted to account for differences in cause granularity between GBD and DEX. Fourth, epidemiologic data were logarithmically interpolated to fill in years not estimated by the GBD study.

To measure changes in disease burden over the study period, prevalence and incidence data were extracted from the GBD 2013 database for the available years (1995, 2000, 2005, 2010, and 2013). Disease experts were consulted to determine which metric should be used for each condition. This metric should represent the number of people who were eligible and likely to be receiving treatment for a cause of illness in a given year. In general, we used prevalence for chronic diseases and incidence for acute illnesses. For example, diabetes is a long-term condition that is controlled by daily treatment. Consequently, prevalence is a more appropriate indicator than incidence because diabetic patients must receive regular care. Alternatively, most cancer treatment occurs within the first months of diagnosis.[9] Once cancer is in remission, a person may technically still be a prevalent case and may be receiving some treatment, but the intensity of treatment is negligible relative to treatment in the first months. Consequently, we used incidence for all cancers. Table 3 contains a list of metrics used for each cause.

Health condition	Disease burden metric
Acute glomerulonephritis	incidence
Acute renal failure	prevalence
Alcohol use disorders	prevalence
Alzheimer's disease and other dementias	prevalence
Animal contact	incidence
Anxiety disorders	prevalence
Aortic aneurysm	prevalence
Appendicitis	incidence
Asthma	prevalence
Atrial fibrillation and flutter	prevalence
Attention-deficit/hyperactivity disorder	prevalence
Autistic spectrum disorders	prevalence
Bipolar disorder	prevalence
Bladder cancer	incidence
Brain and nervous system cancers	incidence
Breast cancer	incidence
Cardiomyopathy and myocarditis	prevalence
Cerebrovascular disease	prevalence
Cervical cancer	incidence
Chronic kidney diseases	prevalence
Chronic obstructive pulmonary disease	prevalence

Cirrhosis of the liver	prevalence
Colon and rectum cancers	incidence
Complications of abortion	incidence
Conduct disorder	prevalence
Congenital anomalies	prevalence
Counseling services	population
Depressive disorders	prevalence
Diabetes mellitus	prevalence
Diarrheal diseases	incidence
Diphtheria	prevalence
Donor services	population
Drowning	incidence
Drug use disorders	prevalence
Eating disorders	prevalence
Encephalitis	incidence
Endocarditis	prevalence
Endocrine, metabolic, blood, and immune disorders	prevalence
Epilepsy	prevalence
Esophageal cancer	incidence
Exposure to mechanical forces	incidence
Falls	incidence
Family planning	population
Fire, heat, and hot substances	incidence
Foreign body	incidence
Gallbladder and biliary diseases	incidence
Gallbladder and biliary tract cancer	incidence
Gastritis and duodenitis	incidence
Gout	prevalence
Gynecological diseases	prevalence
HIV/AIDS	prevalence
Heart failure	prevalence
Hemoglobinopathies and hemolytic anemias	prevalence
Hemolytic disease in fetus and newborn and other neonatal jaundice	prevalence
Hepatitis	prevalence
Hodgkin lymphoma	incidence
Hyperlipidemia	prevalence
Hypertension	prevalence
Hypertensive heart disease	prevalence
Idiopathic intellectual disability	prevalence
Indirect maternal deaths	prevalence
Inflammatory bowel disease	prevalence

Inguinal or femoral hernia	prevalence
Interpersonal violence	incidence
Interstitial lung disease and pulmonary sarcoidosis	prevalence
Intestinal infectious diseases	prevalence
Iodine deficiency	prevalence
Iron-deficiency anemia	prevalence
Ischemic heart disease	prevalence
Kidney cancer	incidence
Larynx cancer	incidence
Leprosy	prevalence
Leukemia	incidence
Liver cancer	incidence
Low back and neck pain	prevalence
Lower respiratory infections	incidence
Malignant skin melanoma	incidence
Maternal hemorrhage	prevalence
Maternal hypertensive disorders	incidence
Maternal sepsis and other pregnancy related infection	incidence
Measles	prevalence
Meningitis	prevalence
Mesothelioma	incidence
Migraine	prevalence
Mouth cancer	incidence
Multiple myeloma	incidence
Multiple sclerosis	prevalence
Nasopharynx cancer	incidence
Neglected tropical diseases and malaria	prevalence
Neonatal encephalopathy (birth asphyxia and birth trauma)	prevalence
Non-Hodgkin lymphoma	incidence
Non-melanoma skin cancer	incidence
Obesity	prevalence
Obstructed labor	incidence
Oral disorders	prevalence
Osteoarthritis	prevalence
Other cardiovascular and circulatory diseases	prevalence
Other chronic respiratory diseases	prevalence
Other digestive diseases	prevalence
Other infectious diseases	prevalence
Other maternal disorders	prevalence
Other mental and behavioral disorders	prevalence
Other musculoskeletal disorders	prevalence

Other neonatal disorders	prevalence
Other neoplasms	incidence
Other neurological disorders	prevalence
Other nutritional deficiencies	prevalence
Other pharynx cancer	incidence
Other transport injuries	incidence
Other unintentional injuries	incidence
Otitis media	incidence
Ovarian cancer	incidence
Pancreatic cancer	incidence
Pancreatitis	incidence
Paralytic ileus and intestinal obstruction	incidence
Parkinson's disease	prevalence
Peptic ulcer disease	incidence
Peripheral vascular disease	prevalence
Pneumoconiosis	prevalence
Poisonings	incidence
Pregnancy and postpartum care	prevalence
Preterm birth complications	prevalence
Prostate cancer	incidence
Protein-energy malnutrition	prevalence
Rheumatic heart disease	prevalence
Rheumatoid arthritis	prevalence
Road injuries	incidence
Schizophrenia	prevalence
Self-harm	incidence
Sense organ diseases	prevalence
Sepsis and other infectious disorders of the newborn baby	prevalence
Septicemia	incidence
Sexually transmitted diseases excluding HIV	prevalence
Skin and subcutaneous diseases	prevalence
Social services	population
Stomach cancer	incidence
Tension-type headache	prevalence
Testicular cancer	incidence
Tetanus	incidence
Thyroid cancer	incidence
Tobacco	prevalence
Trachea, bronchus, and lung cancers	incidence
Tuberculosis	prevalence
Upper respiratory infections	incidence

Urinary diseases and male infertility	prevalence
Uterine cancer	incidence
Varicella	incidence
Vascular intestinal disorders	incidence
Vitamin A deficiency	prevalence
Well dental	population
Well newborn	population
Well person	population
Whooping cough	prevalence

Table 3. Disease burden metrics used for each health condition

Some causes included in the DEX study are not included as causes of disease burden in the GBD study and so do not have prevalence or incidence estimates. These causes of spending include all non-disease causes related to well-care and prevention, four conditions that are classified as risk factors in the GBD study, and three that are considered impairments. These conditions are included in DEX due to their substantial contribution to spending. For all well-care causes except pregnancy, we assigned a prevalence rate of one, to indicate that the entire population has the potential to be receiving this type of well-care. We used the fertility rate as a proxy for the prevalence of pregnancy. The risk factors included in DEX were hypertension, hyperlipidemia, obesity, and tobacco use. While these factors are not themselves considered health conditions, there is considerable spending on them in order to prevent conditions like cardiovascular disease. To obtain burden estimates for risk factors, GBD estimates on the prevalence of risk factors were used. Thresholds developed by GBD scientists were used to classify presence or absence of a risk factor. For example, hypertension was defined as having a systolic blood pressure over 140 mmHg. The impairments included as causes in the DEX study were septicemia, renal failure, and heart failure. These are excluded from the GBD study because they are considered consequences of underlying causes rather than causes themselves. We used the closest proxy available in the GBD for these cases.

There were also some cases where GBD and DEX cause definitions did not match due to differences in the granularity of measurement between the two studies: GBD allows for four levels of cause aggregation, and DEX allows for three. This discrepancy resulted in eight residual “other” causes that did not have prevalence estimates from GBD. For example, the GBD study produces estimates for total neonatal burden and several sub-causes of neonatal burden, but does not include a “neonatal other” category. Where these residual “other” causes remained, we subtracted the sub-causes from each master cause estimated by GBD.

As previously mentioned, the GBD study does not estimate prevalence and incidence for every year from 1996 through 2013. To produce estimates for all years, data were logarithmically interpolated by condition, age, and sex. This approach assumes a constant rate of change between 1995 and 2000 and predicts values for in-between years according to this trend. Because year-to-year differences in epidemiologic data are relatively small, this method is likely to produce reasonable estimates.

While population, prevalence, expenditure, and price are extracted directly from the databases described, the remaining factors were produced by manipulating extracted variables. Specifically, to calculate the population fraction, we divided the population in a given age category by the total

population for that year. To calculate utilization, we divided volume estimates by prevalence or incidence estimates for each condition.

It is important to note that, because of the differences in GBD and DEX data, the total spending increase does not completely match that reported in Dieleman et al. 2016. These modifications were primarily due to the exclusion of instances where the case rate was below 1 case nationwide.

Section 3: Decomposition

We used the decomposition method described by Das Gupta[10] to decompose the contribution of each of the five factors to changes in health spending. This method is based on the calculation of standardized rates in order to eliminate the compositional effects of all other factors in different years. Our data structure enabled the use of this method, since the outcome variable (spending) is the product of the five factors of interest).

We calculate standardized rates for each factor by considering all possible combinations of other factors across time. For example, if only considering two factors, utilization (U) and price (P), and two years, 1996 and 2013, the price-standardized rate in each year would be:

$$1996\ Price\ standardized\ rate\colon\ \frac{P_{2013}+P_{1996}}{2}U_{1996}$$

$$2013\ Price\ standardized\ rate\colon\ \frac{P_{2013}+P_{1996}}{2}U_{2013}$$

The difference between the 1996 price-standardized rate and the 2013 price-standardized rate is the effect of utilization, or the contribution of utilization to changes in the outcome between 1996 and 2013 (below equation).

$$Effect\ of\ Utilization = \frac{P_{2013}+P_{1996}}{2}(U_{2013}-U_{1996})$$

The decomposition for our purposes was performed using the expanded 5-factor equation with calculations adjusted to ensure internal consistency, described elsewhere.[11] The decomposition was completed for each of the condition, age and sex, and type of care stratified groups, and for every possible combination of years (an input into the equation which accounts for multiple populations, as described by Das Gupta).[11] The impact of each driver can be aggregated to assess the impact of the driver for any condition, age and sex group, or type of care of interest. To calculate uncertainty, we performed the decomposition analysis 1,000 times for each of the 1,000 draws of input data.

An outlier detection was conducted in order to stabilize the final decomposition estimates. For each driver and type of care, we compute modified z-score, where:

$$\text{Modified z-score} = \frac{X_{f,e,d}-median(X_{f,e})}{MAD(X_{f,e})} * 0.6745$$

where *f* is a specific function, *e* is a specific driver, and *d* is a draw. Using the threshold defined in Iglewics and Hoaglin (1993),[12] the maximum modified z-score of each draw was computed and was dropped if the absolute computed value within the draw exceeded 3.5. This resulted in 69 of the 1,000 draws being dropped. The point estimate reported is the mean of the remaining 931 draws, while the uncertainty interval is the 2.5th and 97.5th percentile of the full set of 1,000 draws.

Section 4: Code

```
*************************************************************************************************************
// Decomposition Analysis of Disease Expenditure Data
// Description: This code performs the Das Gupta decomposition for every possible combination of years, which is necessary for the method that achieves internal consistency of annual estimates. In Step 1, the initial decomposition is run, which calculates the effect of each driver at the most granular level of data, for every possible combination of years. These data are then used as an input into Step 2, in which the estimates are adjusted for internal consistency over time. This final step will output a file with the amount of spending increase attributable to each of the five drivers, at the age-sex-health condition-type of care level.
*************************************************************************************************************

*************************************************************************************************************
** STEP 1: RUN INITIAL DECOMPOSITION TO CALCULATE EFFECTS OF EACH DRIVER FOR EVERY COMBINATION OF YEARS **
*************************************************************************************************************
// Looping through all possible combinations of years (where year "1" = 1996, year "2" = 1997, etc.)
	forvalues i = 1/17 {
	forvalues j = 2/18 {

	// restrict to yearly combinations that make sense (i.e., only where start year < end year)
		if `i' != `j' & `i' < `j' {

	// set startyear and endyear of the analysis
		local startyear = `i'
		local endyear = `j'

	************************
	** Step 1A: Prepare data **
	************************

			// Load prepared dataset containing values for each of the five drivers and spending by age, sex, health condition, type of care, and year
			use "`prepped_data'", clear

			// recode years to be 1-18 rather than 1996-2013
			replace year = year-1995

			// restrict to the two years we are interested in
			keep if year == `startyear' | year == `endyear'
```

```
// Generate population fraction - keep just one health condition and type of care to get
total population for each year
preserve

keep if acause == "diabetes" & function == "AM"
collapse(sum) population, by(year)
sum population if year == `startyear'
local total_`startyear' = `r(mean)'
sum population if year == `endyear'
local total_`endyear' = `r(mean)'

restore

// fill in with total population values calculated above
gen total_pop = .
replace total_pop = `total_`startyear'' if year == `startyear'
replace total_pop = `total_`endyear'' if year == `endyear'

// Calculate population fraction
gen pop_frac = population/total_pop

// replace age-sex specific population with total population
rename population old_pop
rename total_pop population

// drop all observations where cases are below 1 -- prevalence is too low to allow for
accurate estimation
gen drop = 0
replace drop = 1 if cases < 1

bysort acause function age sex: egen prob_cases = sum(drop)

count if prob_cases > 0 & !regexm(acause, "neo_") & function != "LT"
drop if prob_cases > 0

drop drop prob_cases

// Keep relevant variables
keep year population epi_rate util_rate price expend acause age sex function pop_frac
order acause age sex function year population pop_frac epi_rate util_rate price expend
sort acause age sex function year
```

****

```
** Step 1B: Run decomposition **
*****************************

        // reshape wide so we have start year and end year variables for each factor
        reshape wide population pop_frac epi_rate util_rate price expend, i(function acause sex
        age) j(year)

        // loop through five drivers of interest
        forvalues execute = 1/5 {
                noisily di "On loop `execute'/4.. " _c

            // Set variable names as locals for this iteration

                // Factor 1 - Population growth
                if `execute' == 1 {
                        local exp "demo"
                        local var1 "population"
                        local var2 "epi_rate"
                        local var3 "util_rate"
                        local var4 "`middle'price"
                        local var5 "pop_frac"
                }

                // Factor 2 - Epidemiology: Prevalence/Incidence
                if `execute' == 2 {
                        local exp "epi"
                        local var1 "epi_rate"
                        local var2 "population"
                        local var3 "util_rate"
                        local var4 "`middle'price"
                        local var5 "pop_frac"
                }

                // Factor 3 - Utilization rate
                if `execute' == 3 {
                        local exp "util"
                        local var1 "util_rate"
                        local var2 "population"
                        local var3 "epi_rate"
                        local var4 "`middle'price"
                        local var5 "pop_frac"
                }

                // Factor 4 - Service price & intensity
```

```
if `execute' == 4 {
        local exp "price"
        local var1 "`middle'price"
        local var2 "population"
        local var3 "epi_rate"
        local var4 "util_rate"
        local var5 "pop_frac"
}

// Factor 5 - Population aging
if `execute' == 5 {
        local exp "frac"
        local var1 "pop_frac"
        local var2 "population"
        local var3 "epi_rate"
        local var4 "util_rate"
        local var5 "`middle'price"
}

// Calculate "Q" for each factor
        gen double `var1'_func_`i'_to_`j' =
(`var2'`endyear'*`var3'`endyear'*`var4'`endyear'*`var5'`endyear' + ///
`var2'`startyear'*`var3'`startyear'*`var4'`startyear'*`var5'`startyear')/5 + ///
(`var2'`endyear'*`var3'`endyear'*`var4'`endyear'*`var5'`startyear' + ///
`var2'`endyear'*`var3'`endyear'*`var4'`startyear'*`var5'`endyear' + ///
`var2'`endyear'*`var3'`startyear'*`var4'`endyear'*`var5'`endyear' + ///
`var2'`startyear'*`var3'`endyear'*`var4'`endyear'*`var5'`endyear' + ///
`var2'`startyear'*`var3'`startyear'*`var4'`startyear'*`var5'`endyear' + ///
`var2'`startyear'*`var3'`startyear'*`var4'`endyear'*`var5'`startyear' + ///
`var2'`startyear'*`var3'`endyear'*`var4'`startyear'*`var5'`startyear'+ ///
`var2'`endyear'*`var3'`startyear'*`var4'`startyear'*`var5'`startyear')/20 + ///
(`var2'`endyear'*`var3'`endyear'*`var4'`startyear'*`var5'`startyear' + ///
`var2'`endyear'*`var3'`startyear'*`var4'`endyear'*`var5'`startyear' + ///
`var2'`endyear'*`var3'`startyear'*`var4'`startyear'*`var5'`endyear' + ///
`var2'`startyear'*`var3'`startyear'*`var4'`endyear'*`var5'`endyear' + ///
`var2'`startyear'*`var3'`endyear'*`var4'`startyear'*`var5'`endyear' + ///
`var2'`startyear'*`var3'`endyear'*`var4'`endyear'*`var5'`startyear')/30

// Calculate effect of each driver - multiply Q by observed difference between two years
gen double `var1'_effect_`i'_to_`j' = `var1'_func*(`var1'`endyear'-`var1'`startyear')

}

// Total effect of all factors to get the expenditure change from year i to year j
```

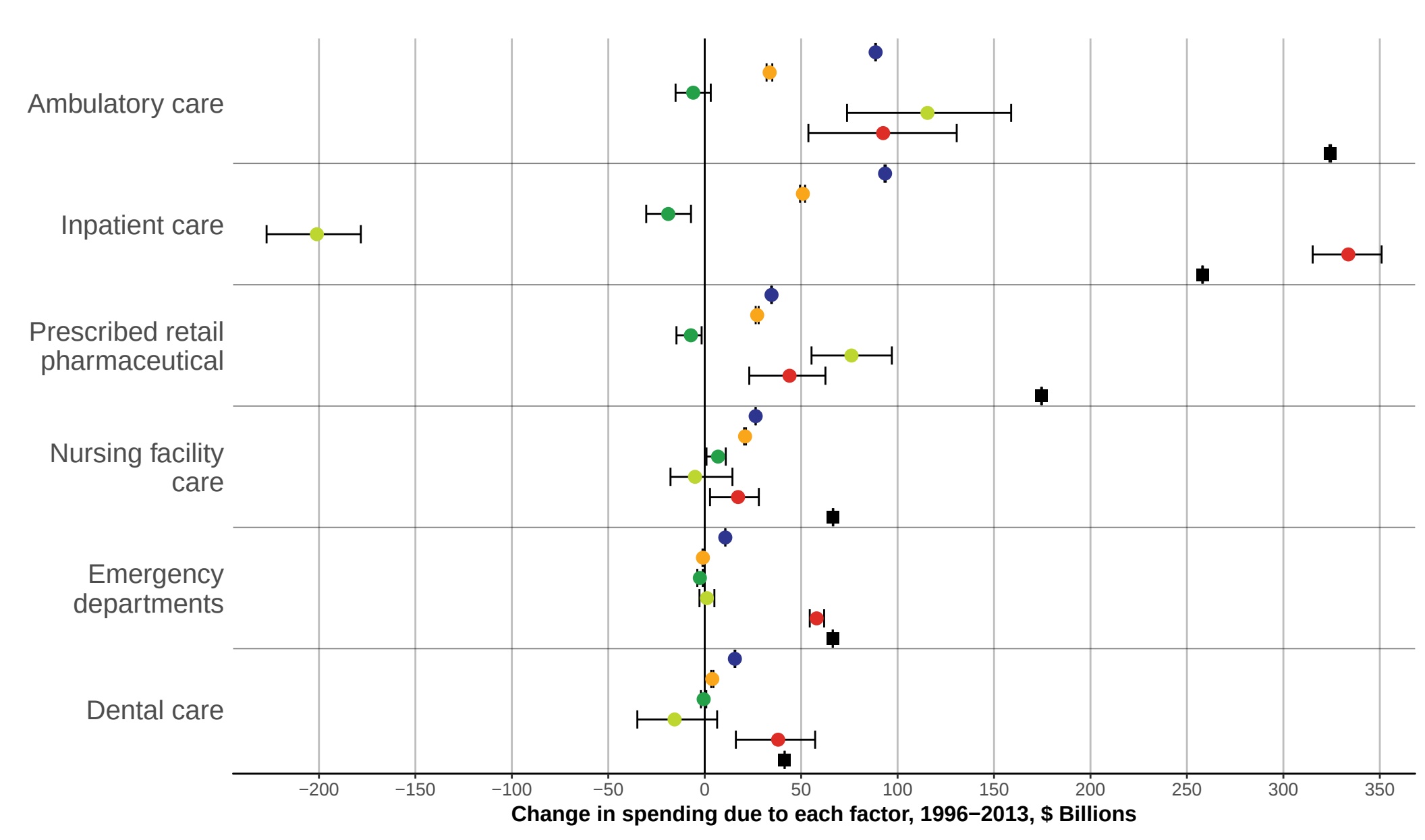
```
		egen double sum_effect_`i'_to_`j' = rowtotal(*_effect*)

	// save data for use in later analysis
	tempfile results_`startyear'_`endyear'
	save `results_`startyear'_`endyear'', replace



			}
		}
	}

*************************************************************************************
****
** STEP 2: COMPILE DATA AND CALCULATE EFFECTS USING DAS GUPTA EQUATION FOR INTERNAL
CONSISTENCY **
*************************************************************************************
****

**********************************
** Step 2A: Merge tempfiles created above **
**********************************
// start with years 1 to 2, and merge all subsequent combinations
use "`results_1_2'", clear

tempfile all_data
save `all_data', replace

forvalues i = 1/17 {
forvalues j = 2/18 {

	if `i' != `j' & `i' < `j' {
	use `all_data', clear

	merge 1:1 acause function sex age using `results_`i'_`j'', nogen

	save `all_data', replace
}
}
}

// drop if missing - occurs when GBD or DEX do not estimate any values for a given year combination (
0.5% of data)
egen miss = rowmiss(*effect*)
```

```
drop if miss > 0

*************************************************************
** Step 2B: Calculate effects of each driver for one-year increments **
*************************************************************
// first get "backwards in time" effects as variables
foreach n in "population_effect" "pop_frac_effect" "epi_rate_effect" "util_rate_effect" "price_effect" {
	forvalues i = 1/17 {
	forvalues j = 2/18 {

		if `i' != `j' & `i' < `j' {
		 gen `n'_`j'_to_`i' = -`n'_`i'_to_`j'
		}
	}
	}
}

// next calculate the terms for the numerator of the Das Gupta equation for internal consistency
foreach n in "population_effect" "pop_frac_effect" "epi_rate_effect" "util_rate_effect" "price_effect" {
	forvalues i = 1/17 {

		local j = `i'+1

		forvalues k = 1/18 {
			if (`k' != `j' & `k' != `i') {
				di "I:`i' J:`j' K:`k'"
				gen double `n'_term`k'_`i'`j' = `n'_`i'_to_`j' + `n'_`j'_to_`k' - `n'_`i'_to_`k'
			}
		}

	// calculate numerator = sum of the 16 effects calculated above
	egen double `n'_num_`i'`j' = rowtotal(`n'_term*_`i'`j')

	// calculate final effect
	gen double `n'_`i'`j' = `n'_`i'_to_`j' - (`n'_num_`i'`j'/18)

	}
}

// add up all factor effects to get final factor effects from year 1 to 18.
foreach n in "population_effect" "pop_frac_effect" "epi_rate_effect" "util_rate_effect" "price_effect" {
	egen final_`n' = rowtotal(`n'_12 `n'_23 `n'_34 `n'_45 `n'_56 `n'_67 `n'_78 `n'_89 `n'_910
`n'_1011 `n'_1112 `n'_1213 `n'_1314 `n'_1415 `n'_1516 `n'_1617 `n'_1718)
}
```

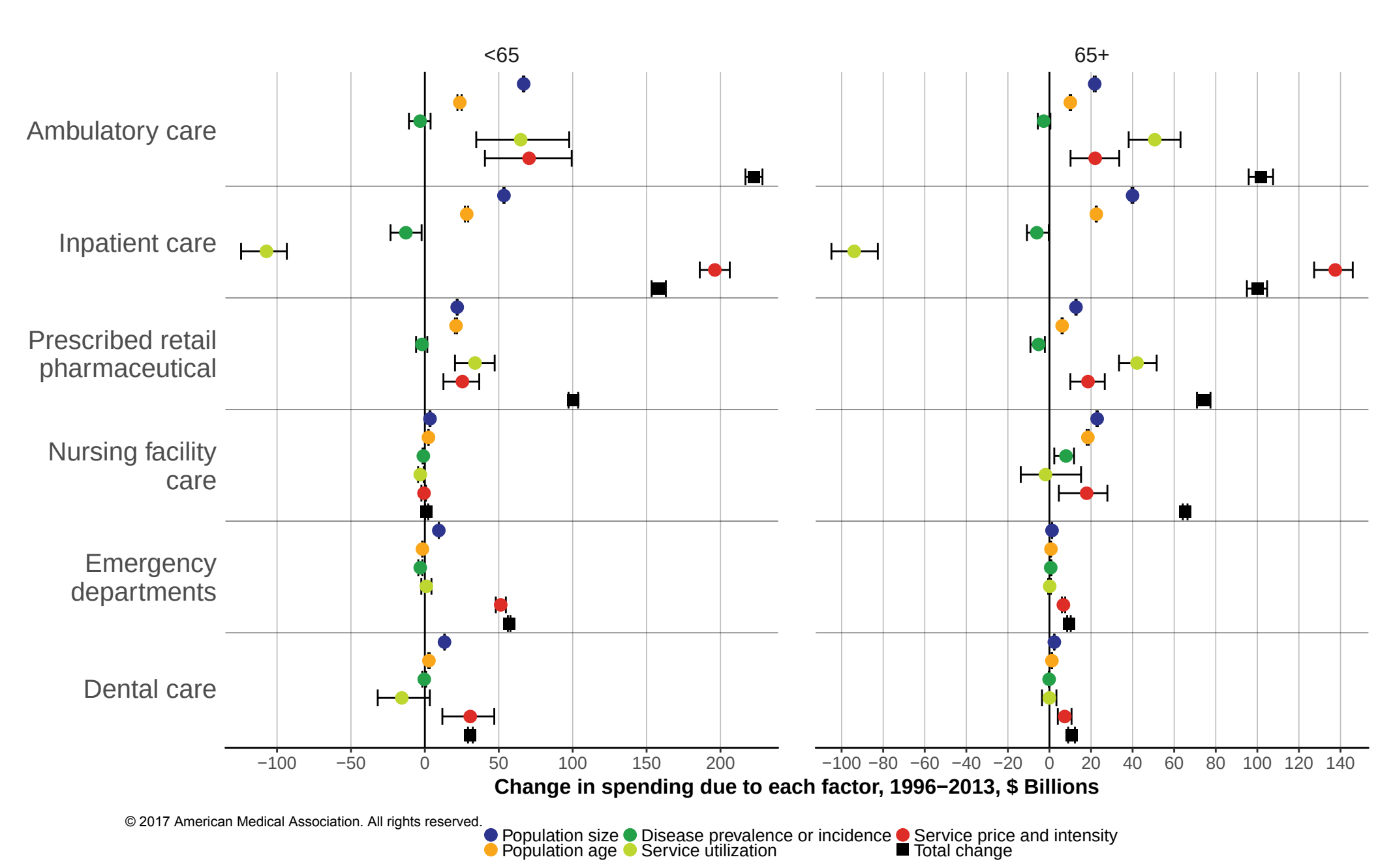
```
egen final_effect = rowtotal(final_*)

// Keep variables that we want (just one-year increments, not all time periods used in above calculation)
foreach n in "population_effect" "pop_frac_effect" "epi_rate_effect" "util_rate_effect" "price_effect" {
        local vars_`n' `n'_12 `n'_23 `n'_34 `n'_45 `n'_56 `n'_67 `n'_78 `n'_89 `n'_910 `n'_1011 `n'_1112
`n'_1213 `n'_1314 `n'_1415 `n'_1516 `n'_1617 `n'_1718
}
local keep_vars `vars_population_effect' `vars_pop_frac_effect' `vars_epi_rate_effect'
`vars_util_rate_effect' `vars_price_effect'

keep function acause sex age final_* `keep_vars'

save "compiled_results.dta", replace
```

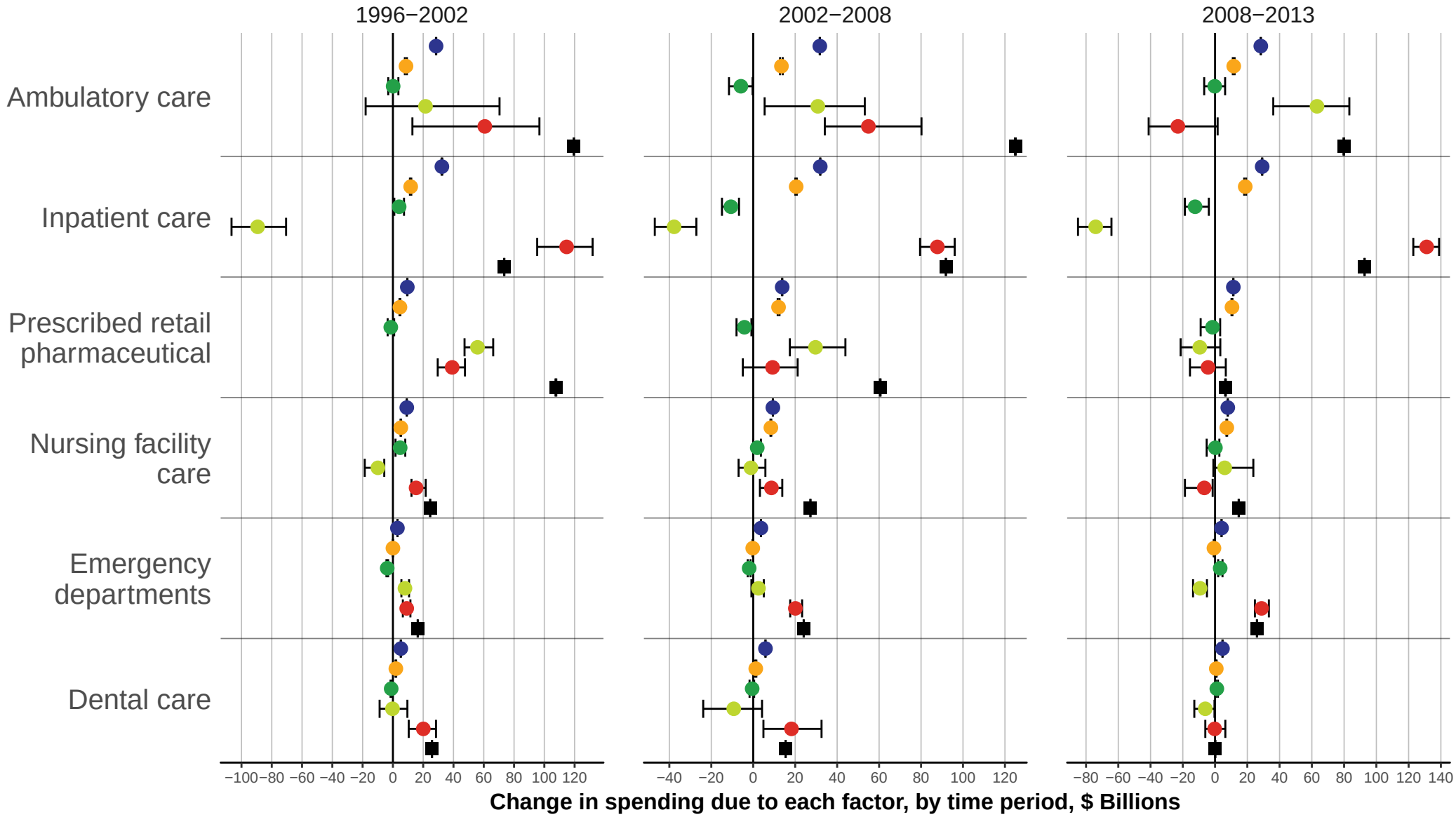
Section 5: Results

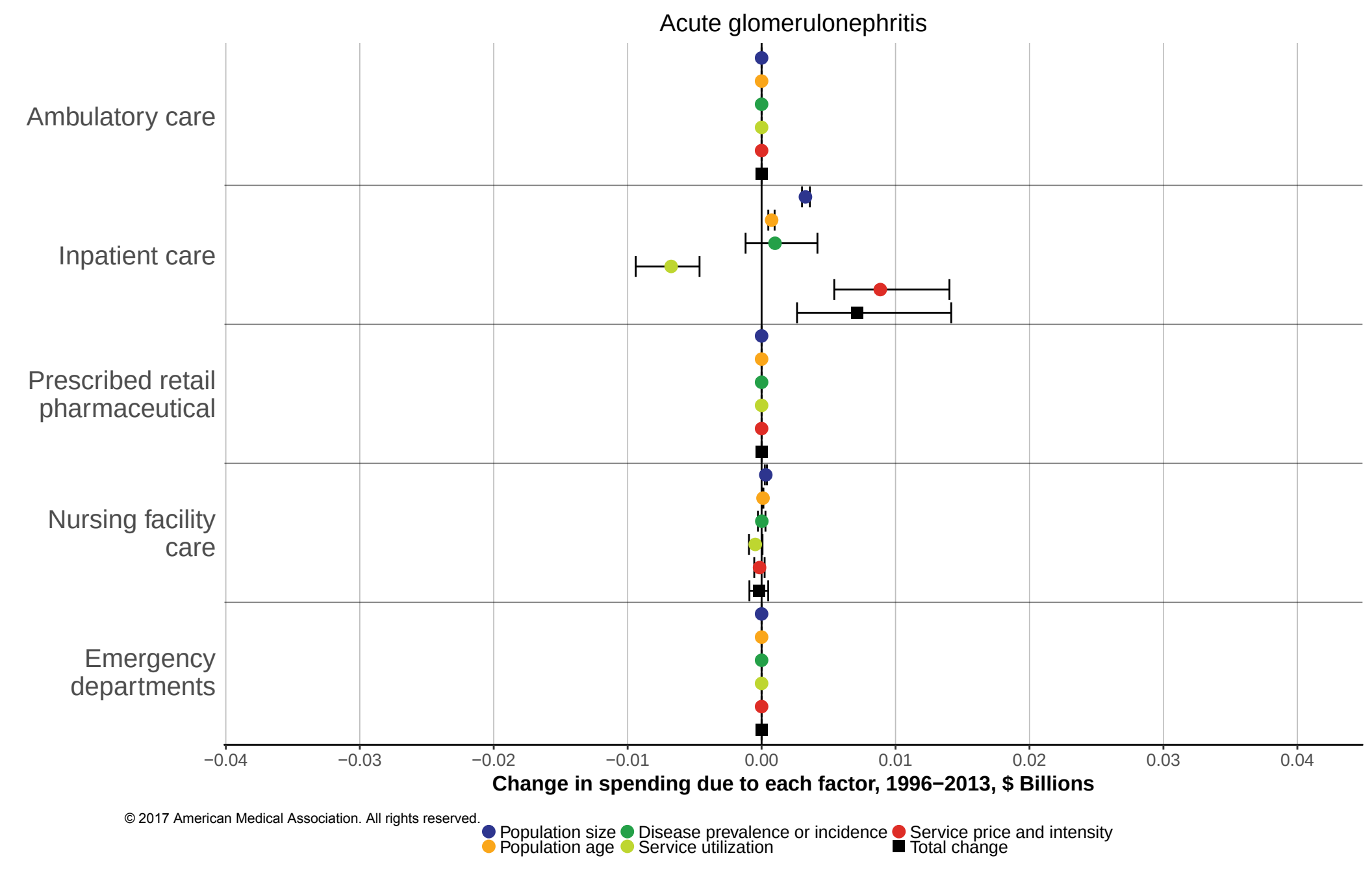
The following series of figures show all the figures from the main manuscript including uncertainty intervals, in addition to health condition-specific decomposition for each of the 150 health conditions included in the decomposition.

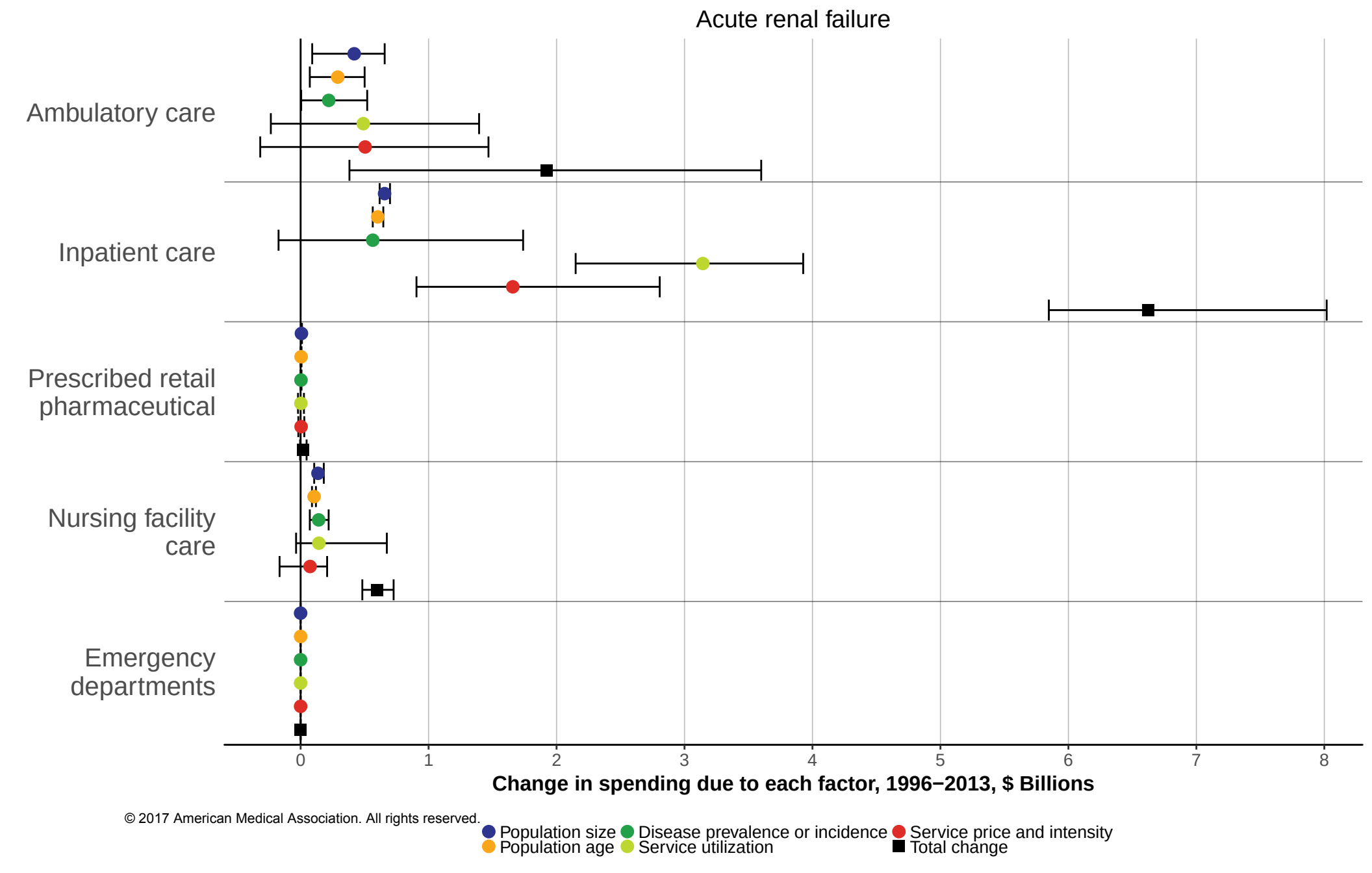


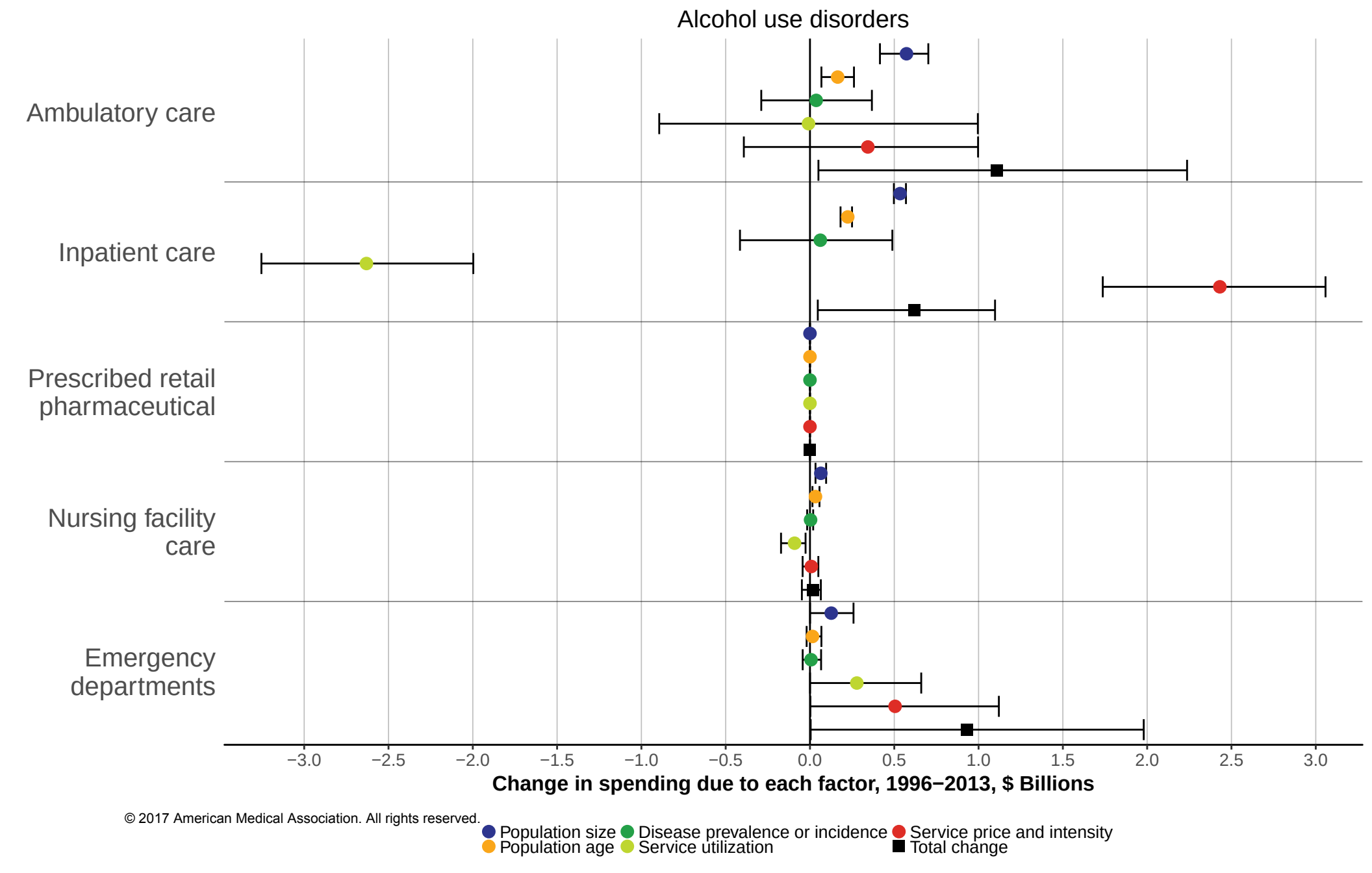
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

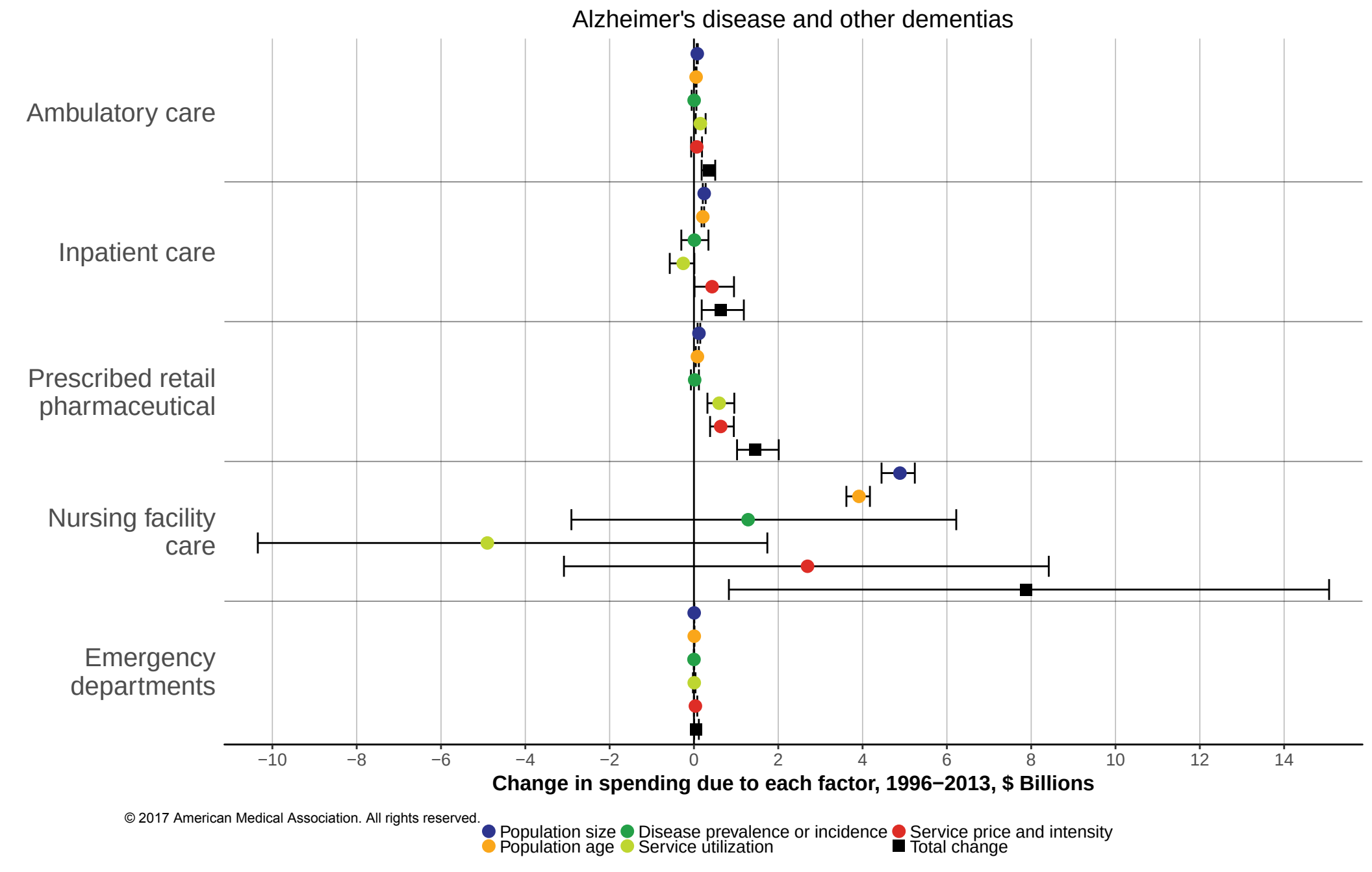


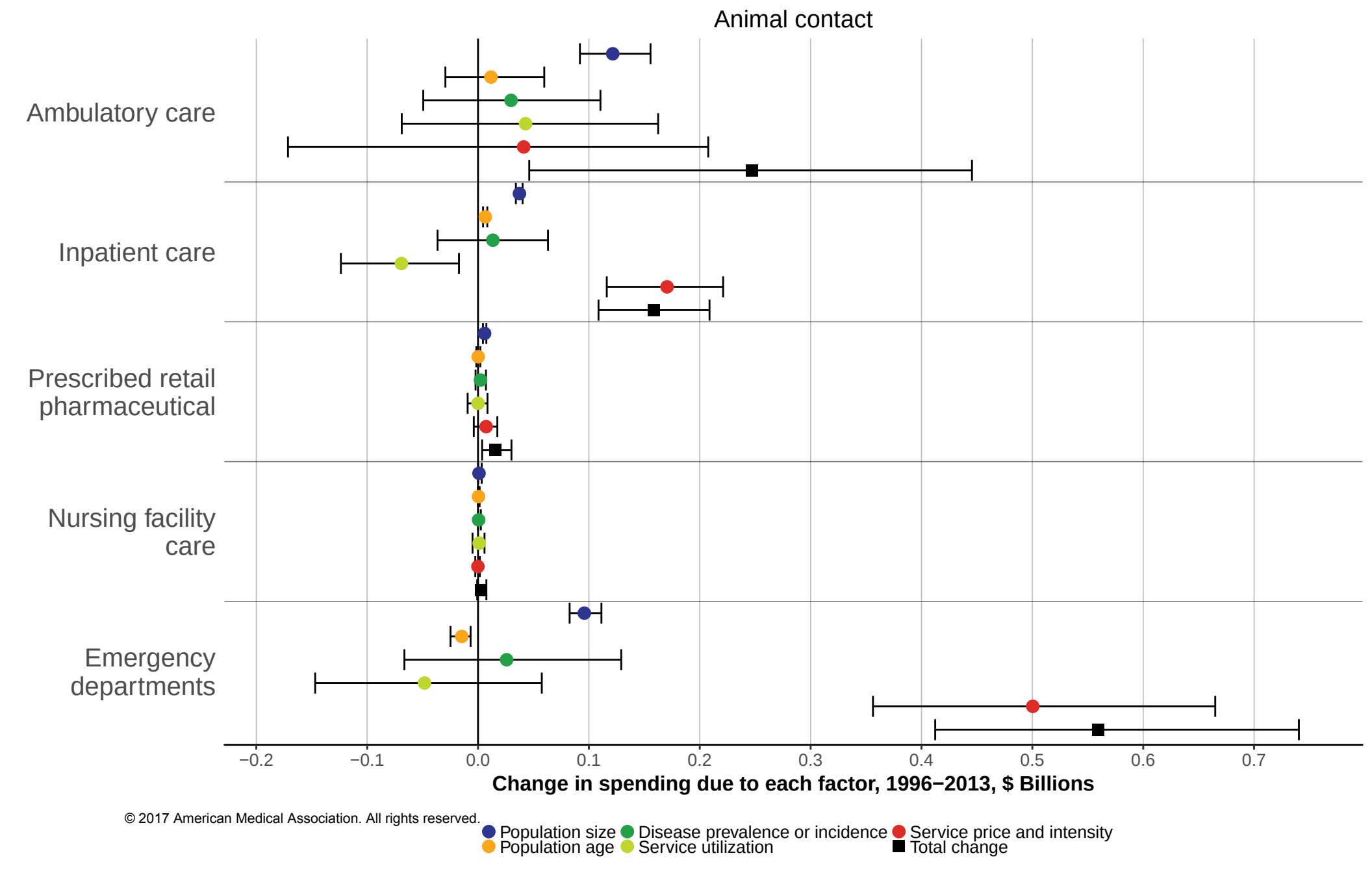


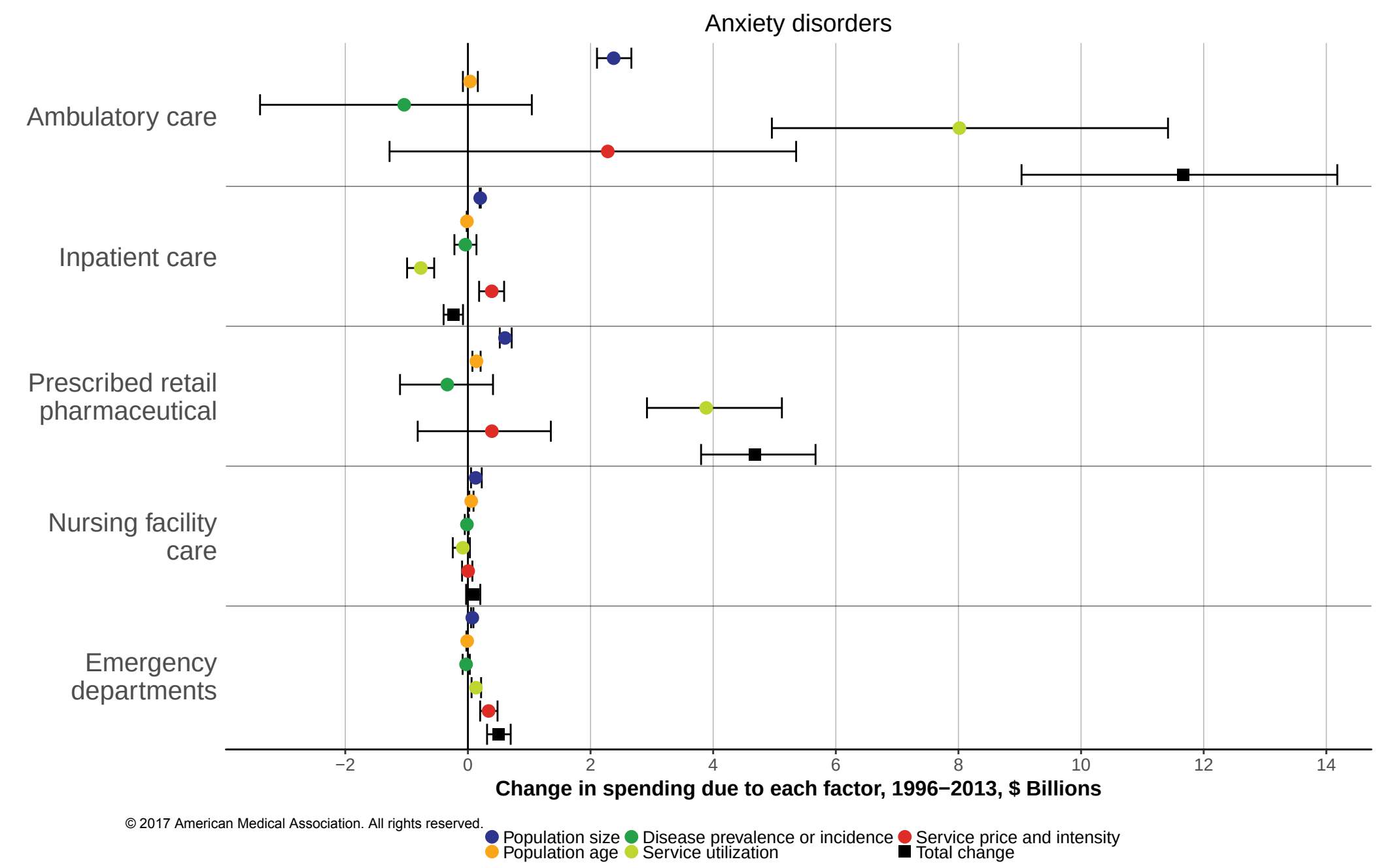


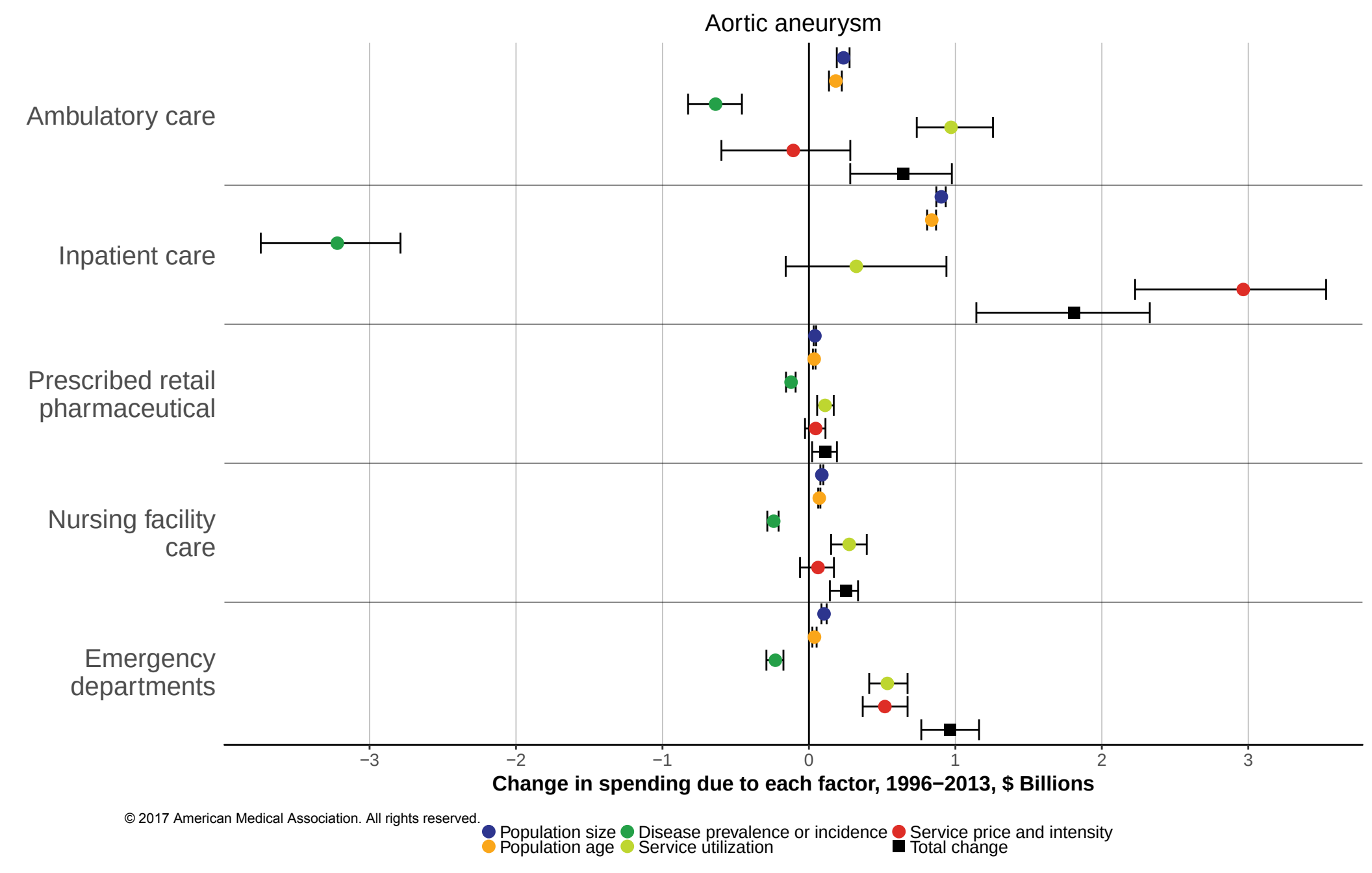


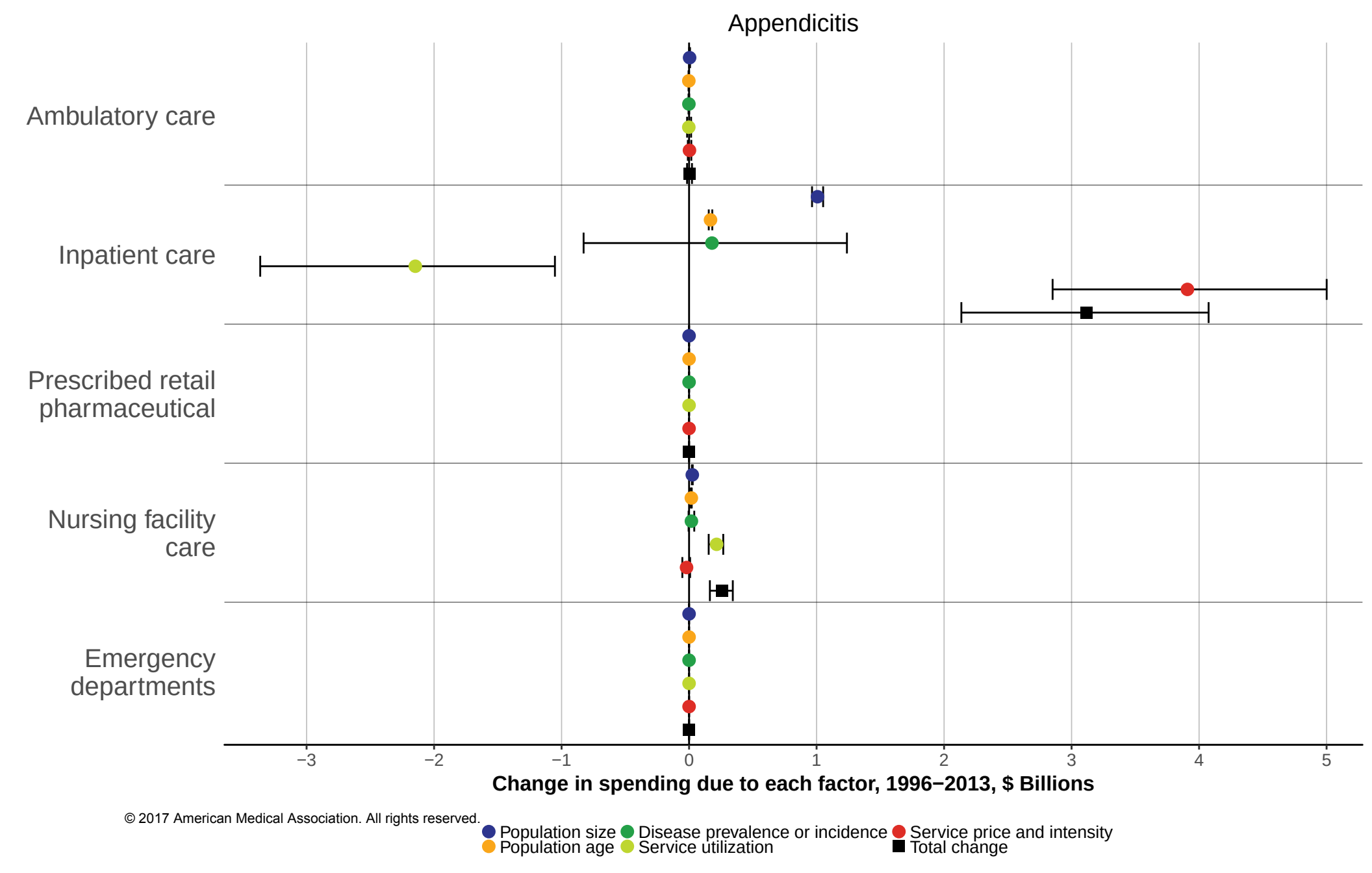


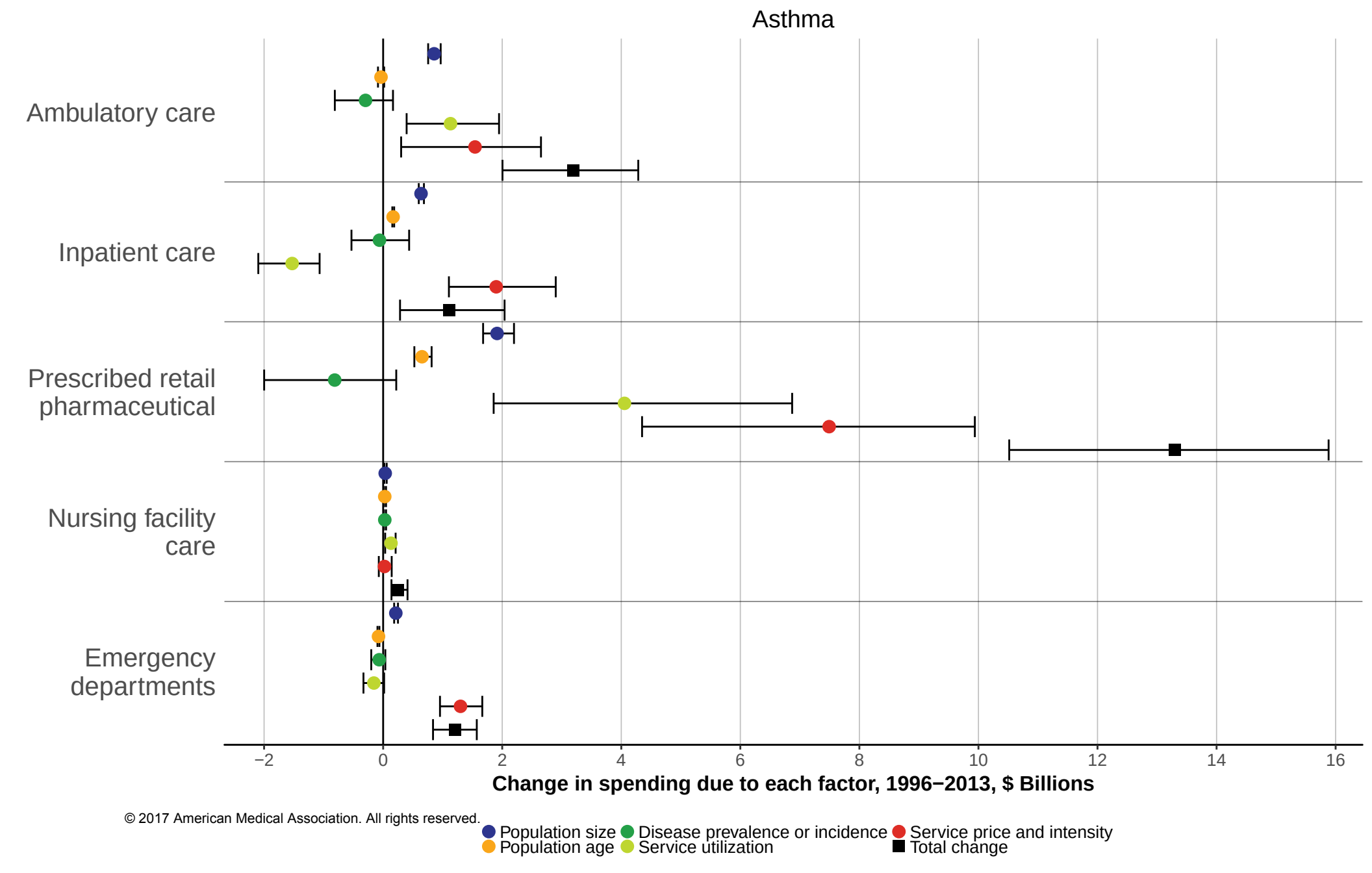


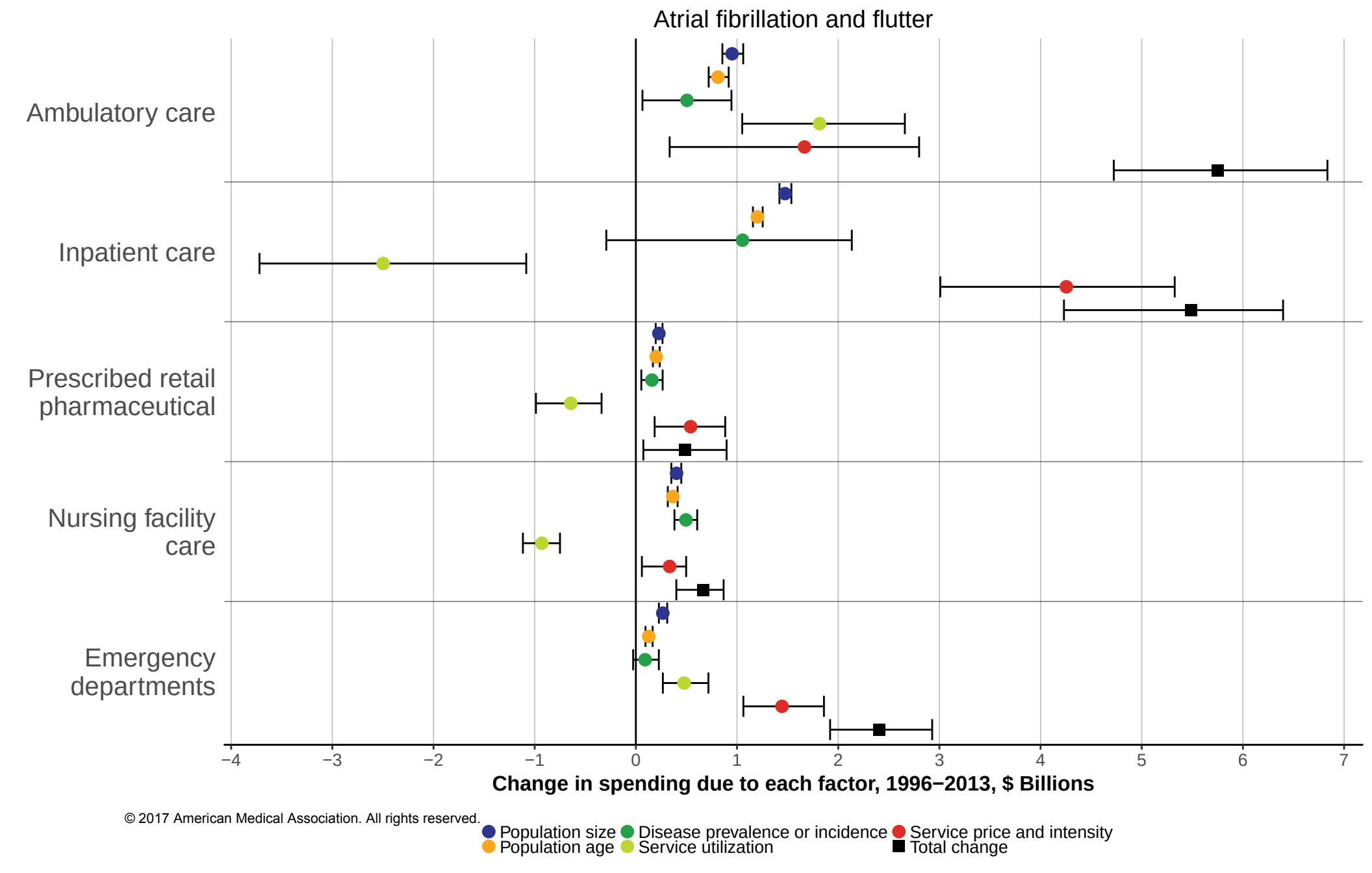


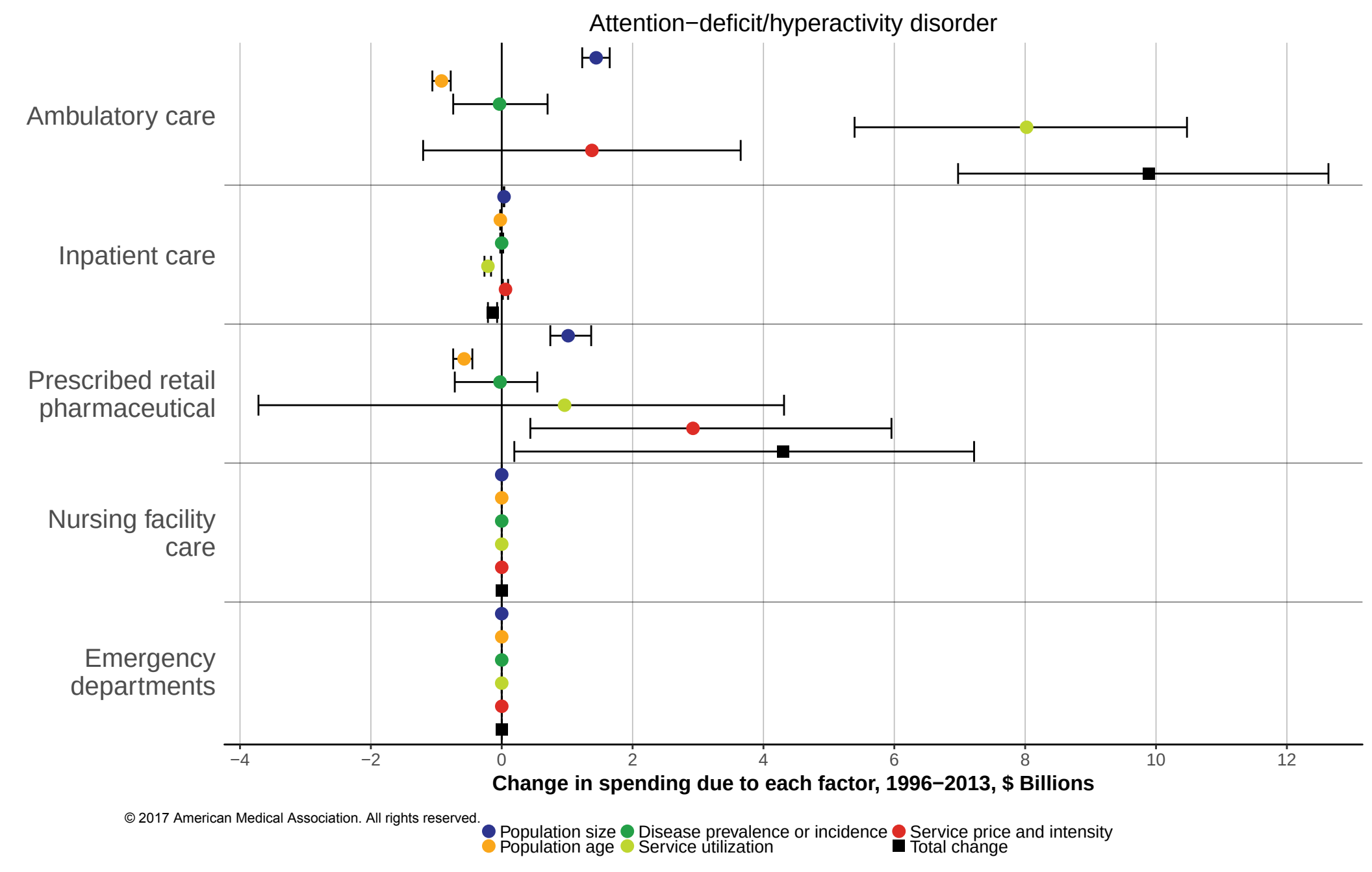


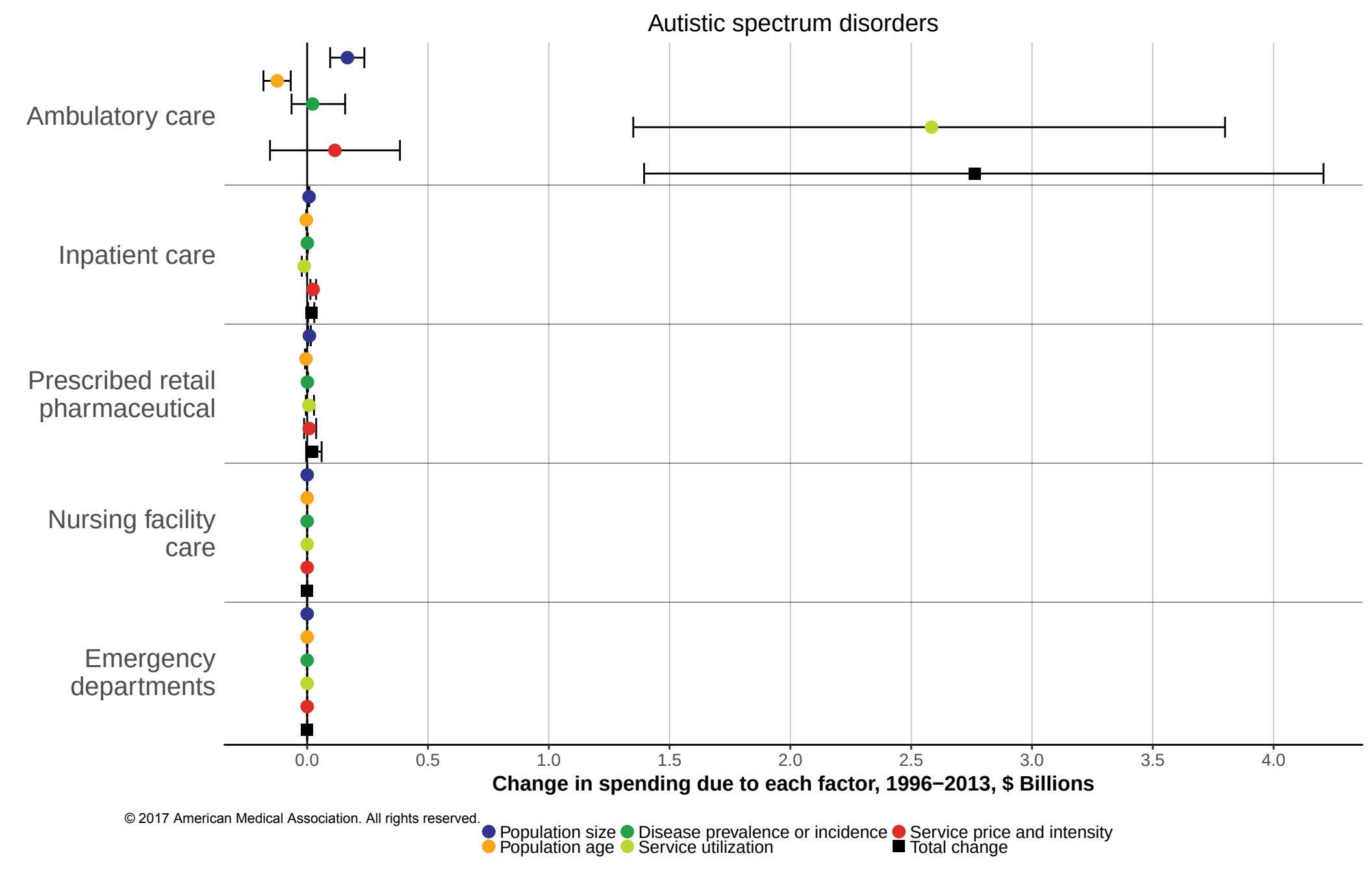


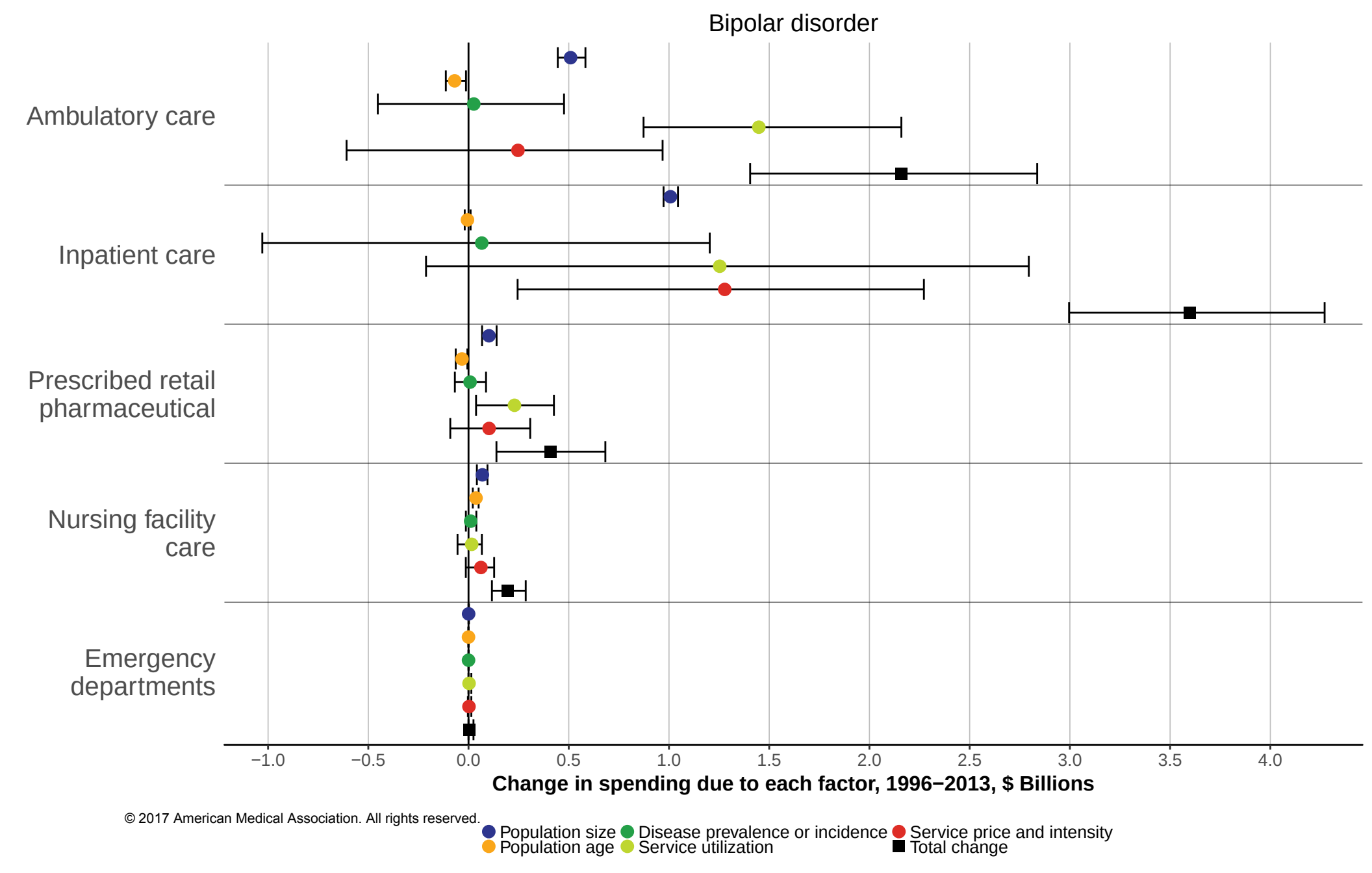


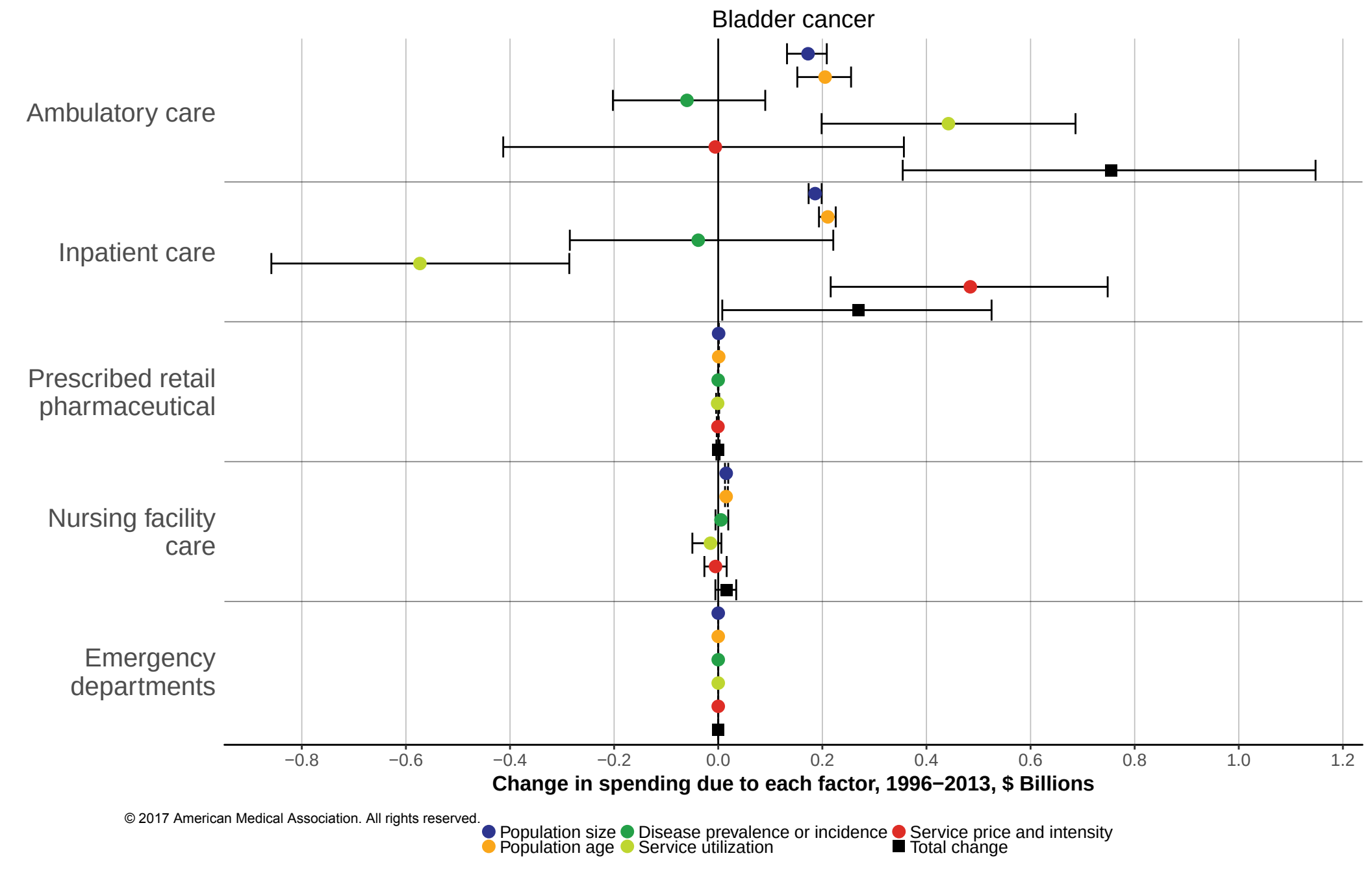


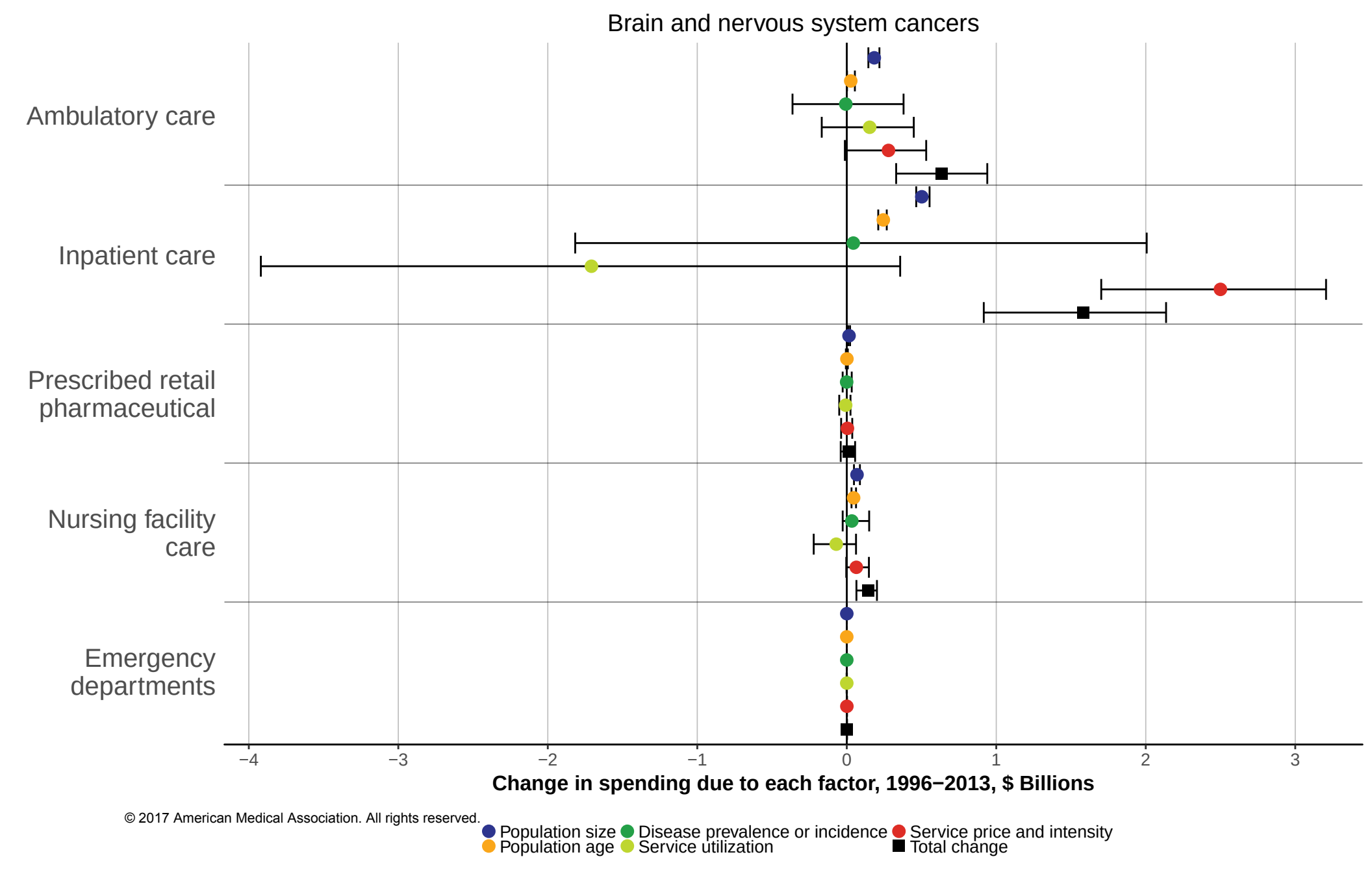


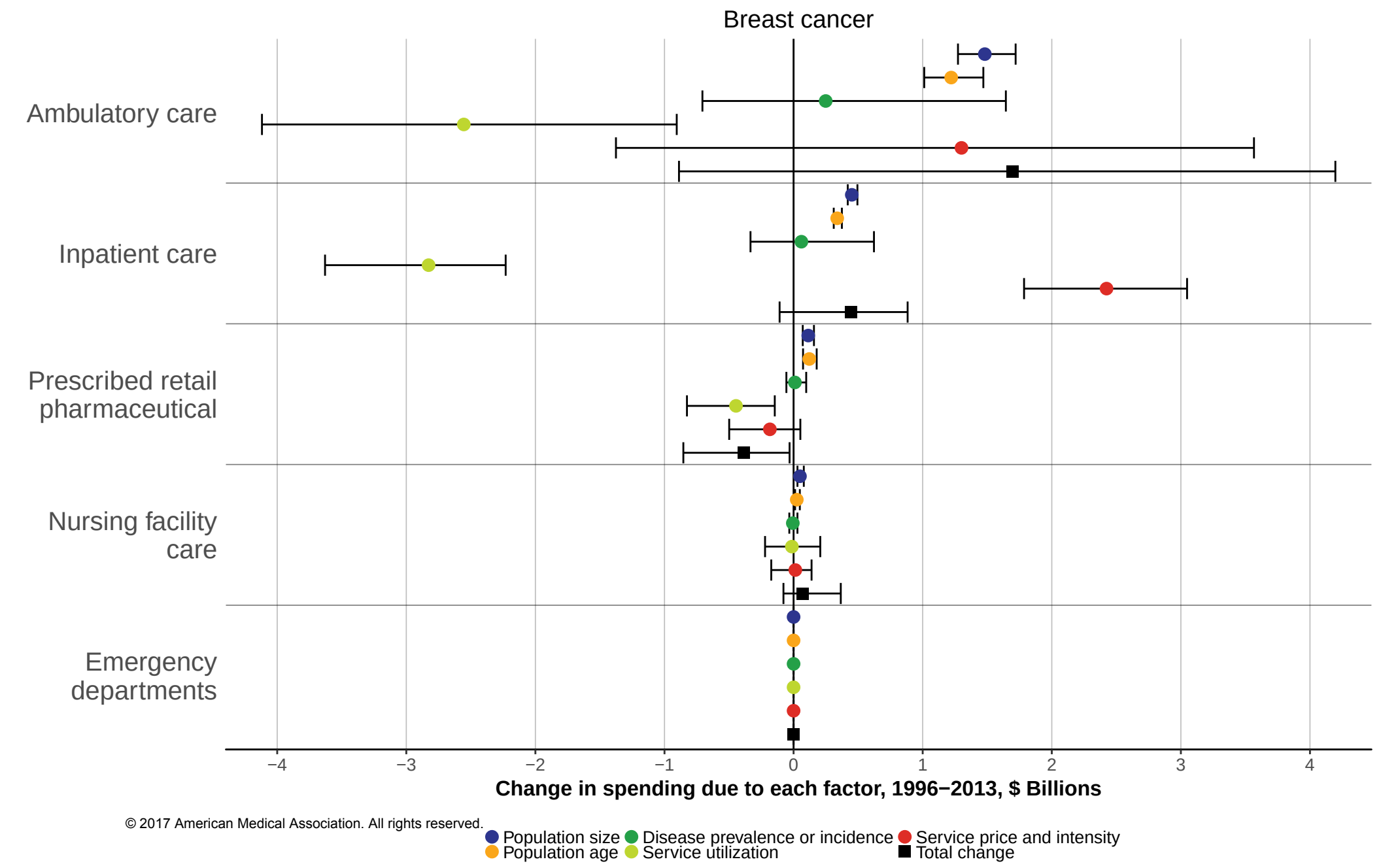


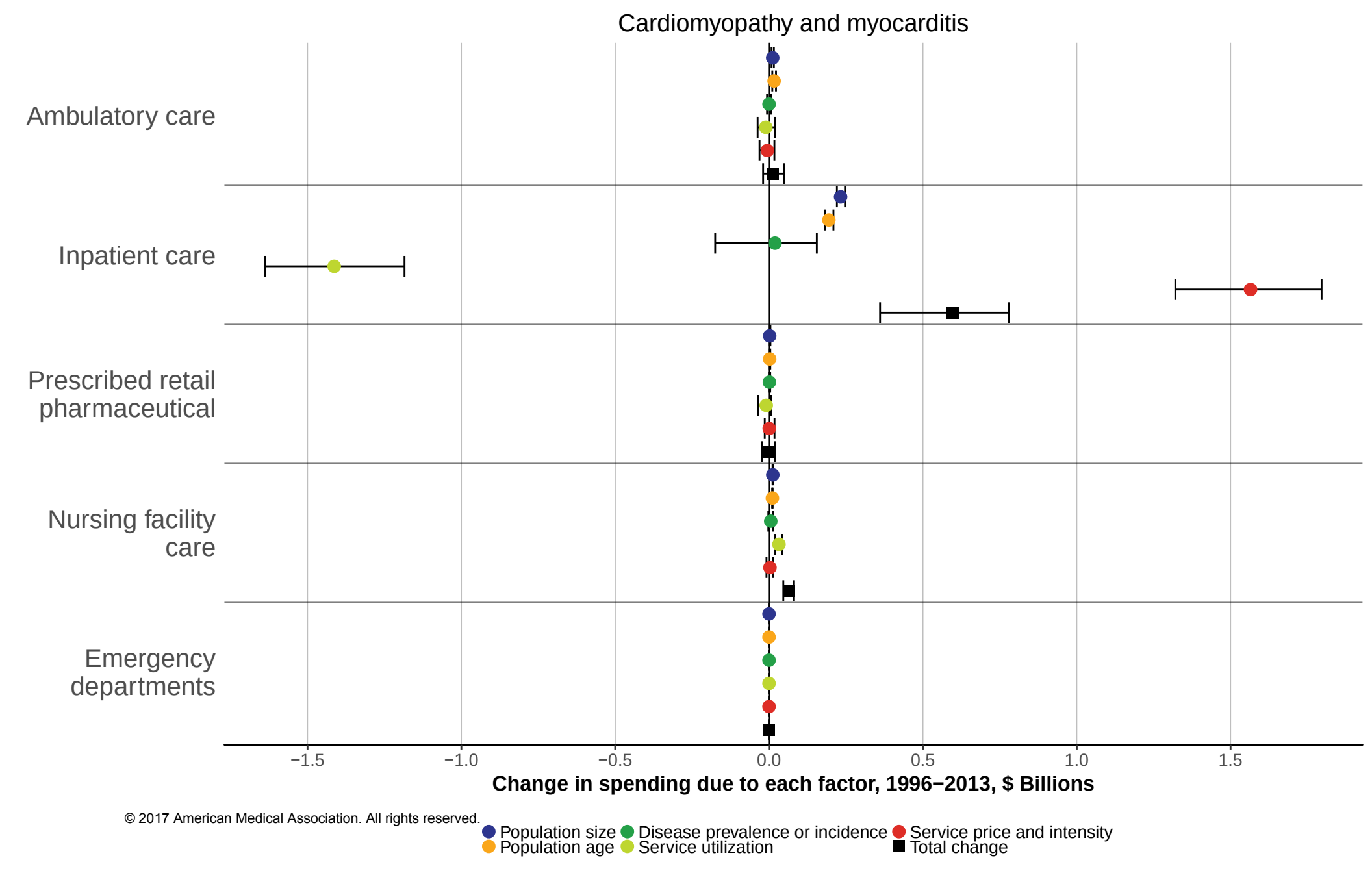


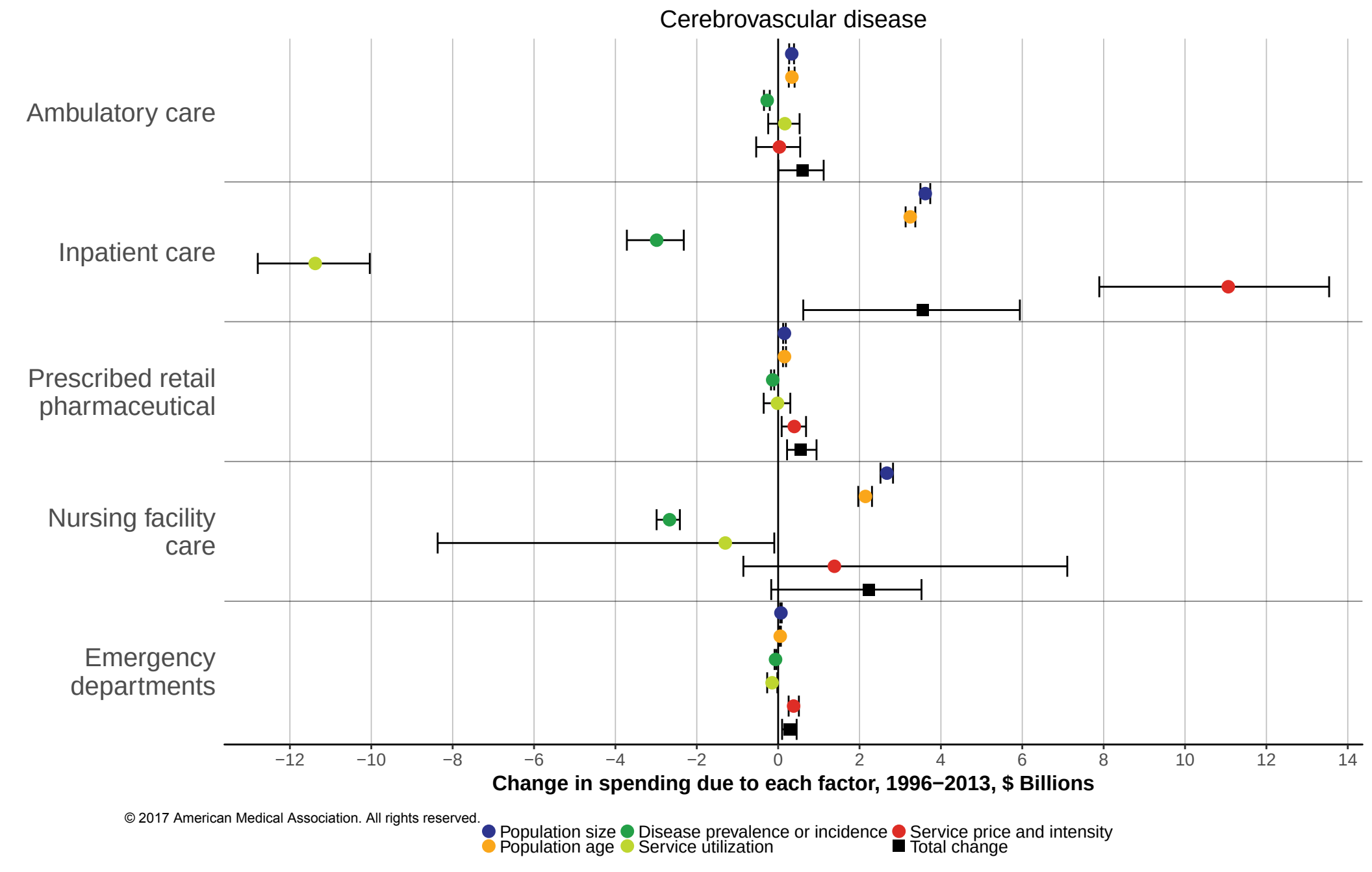




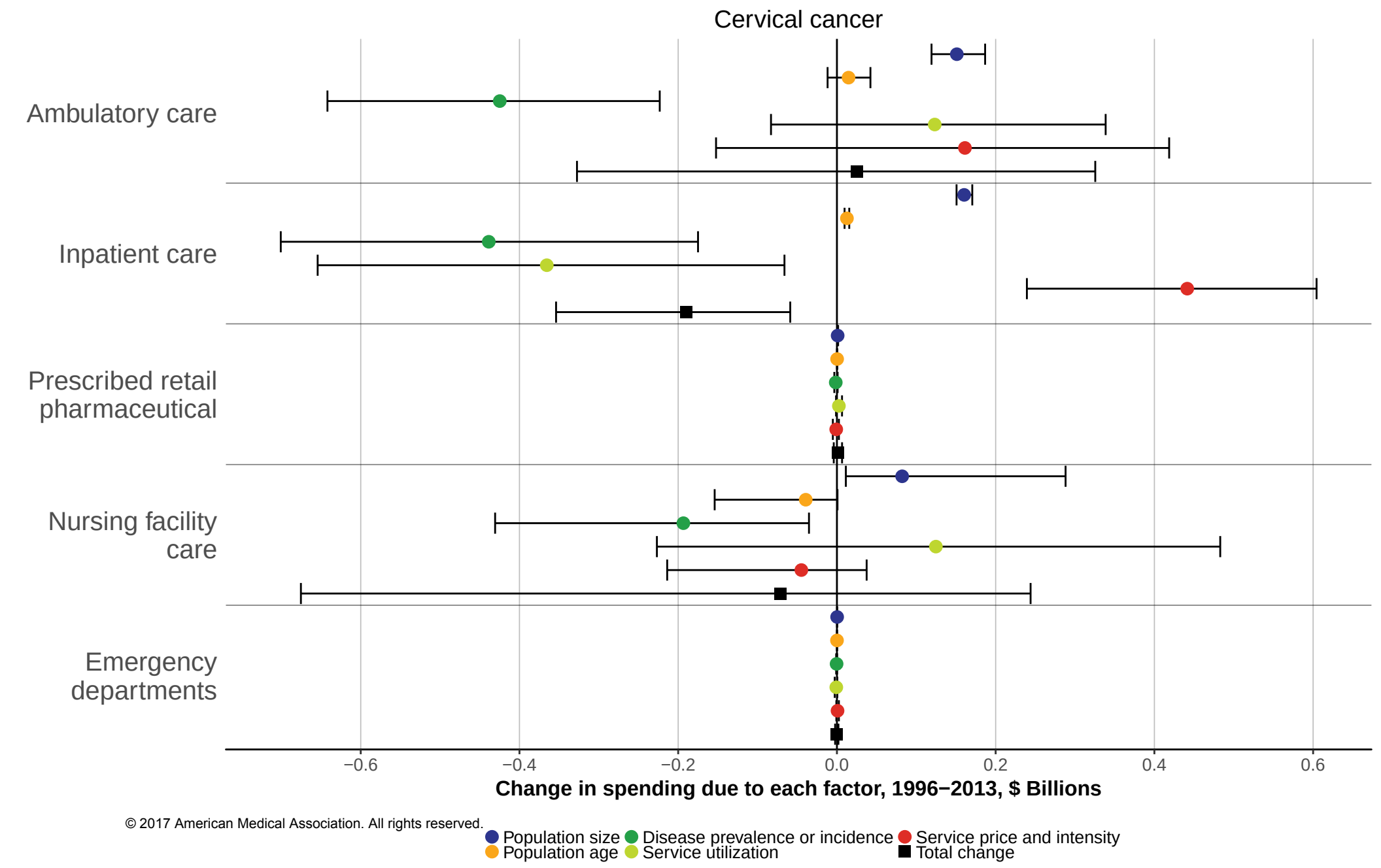


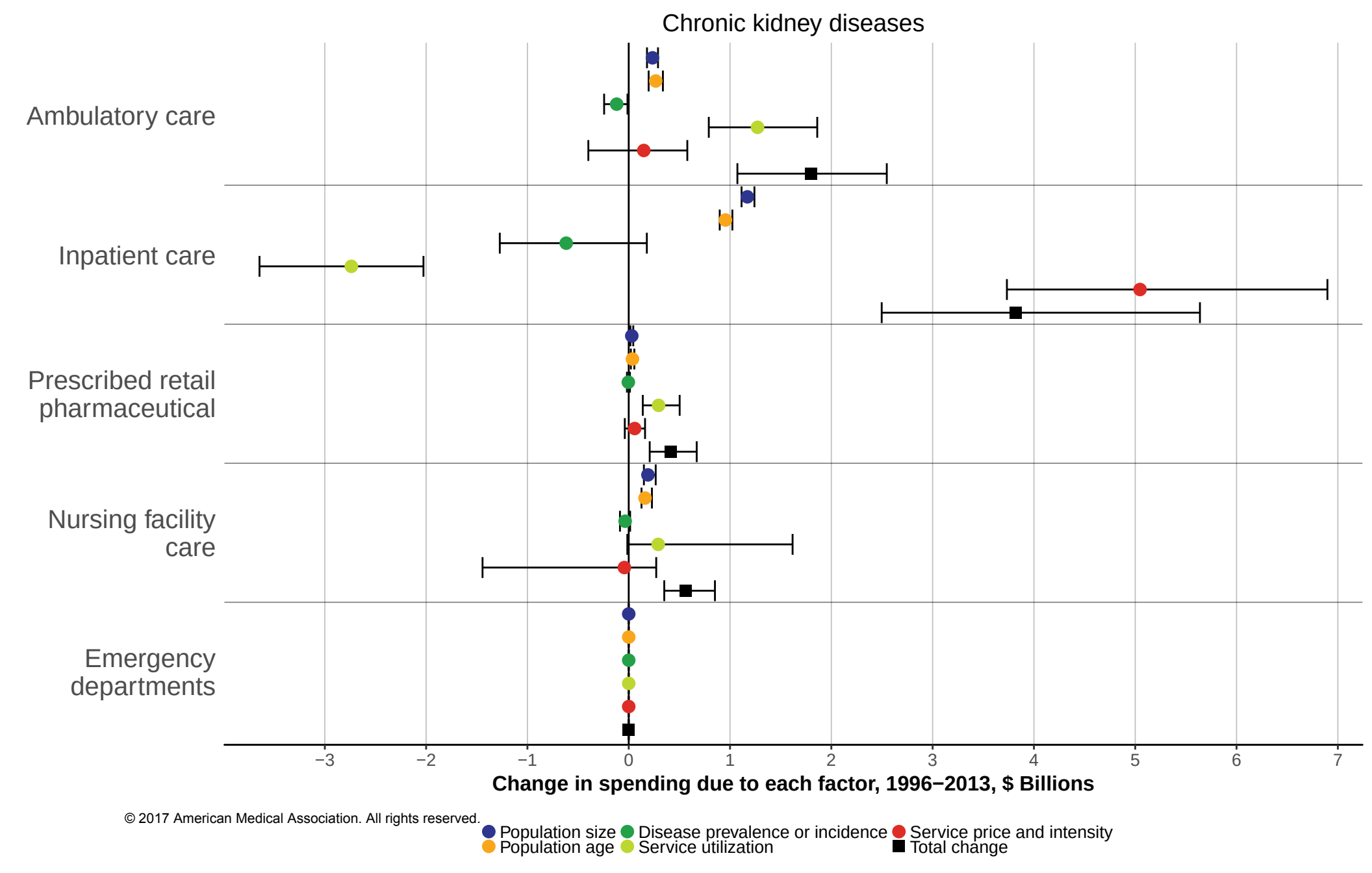


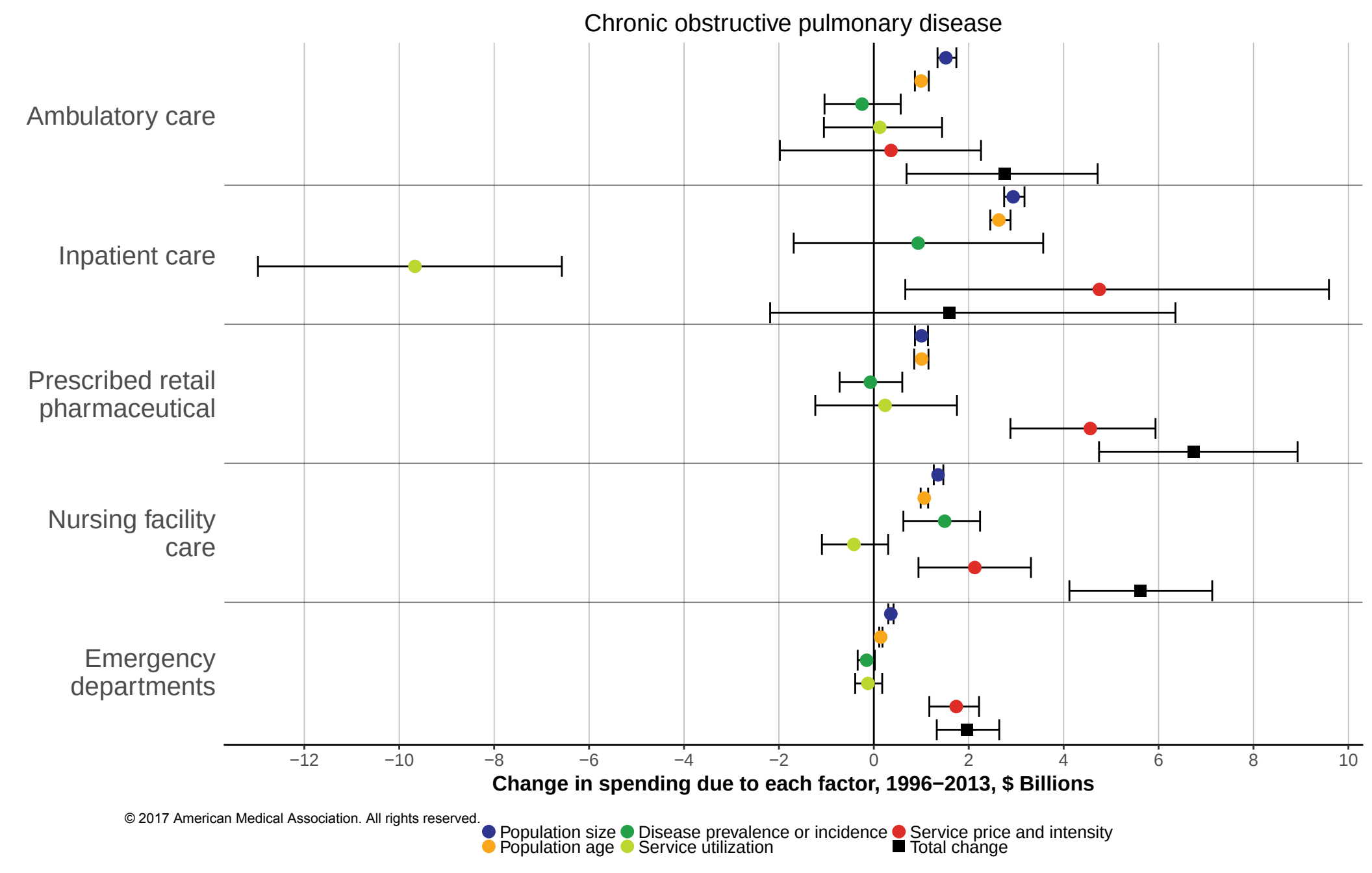


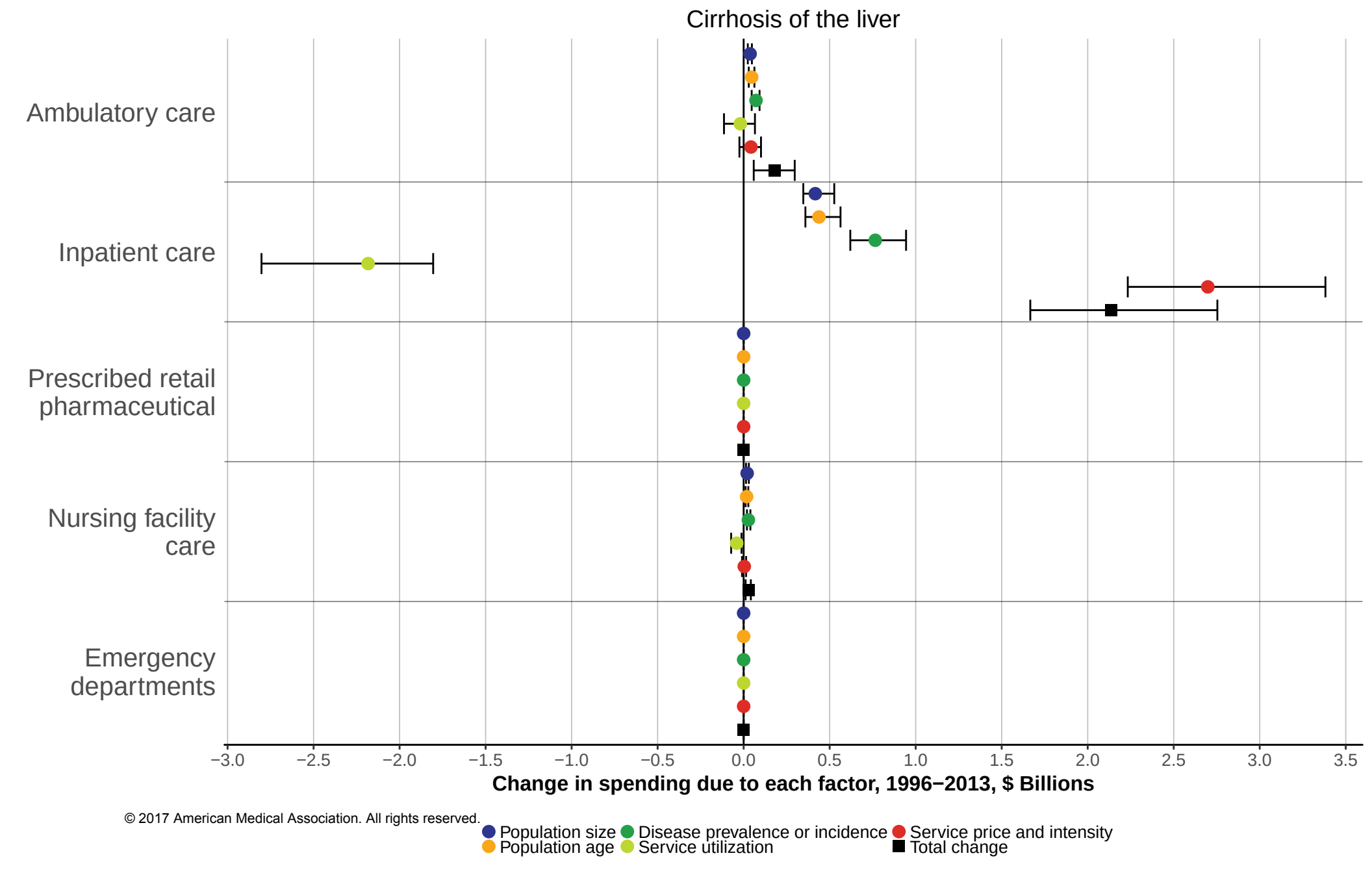


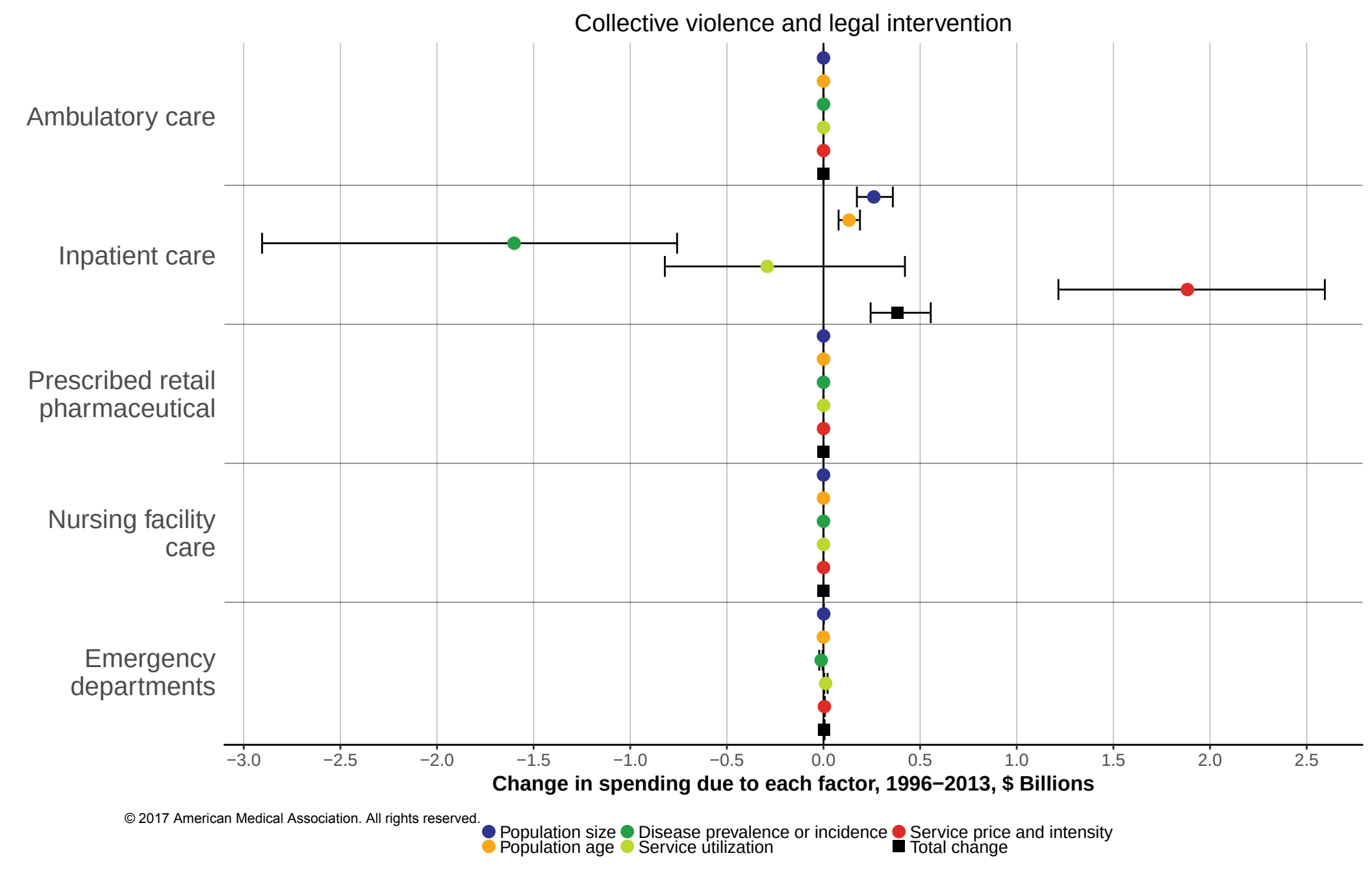
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

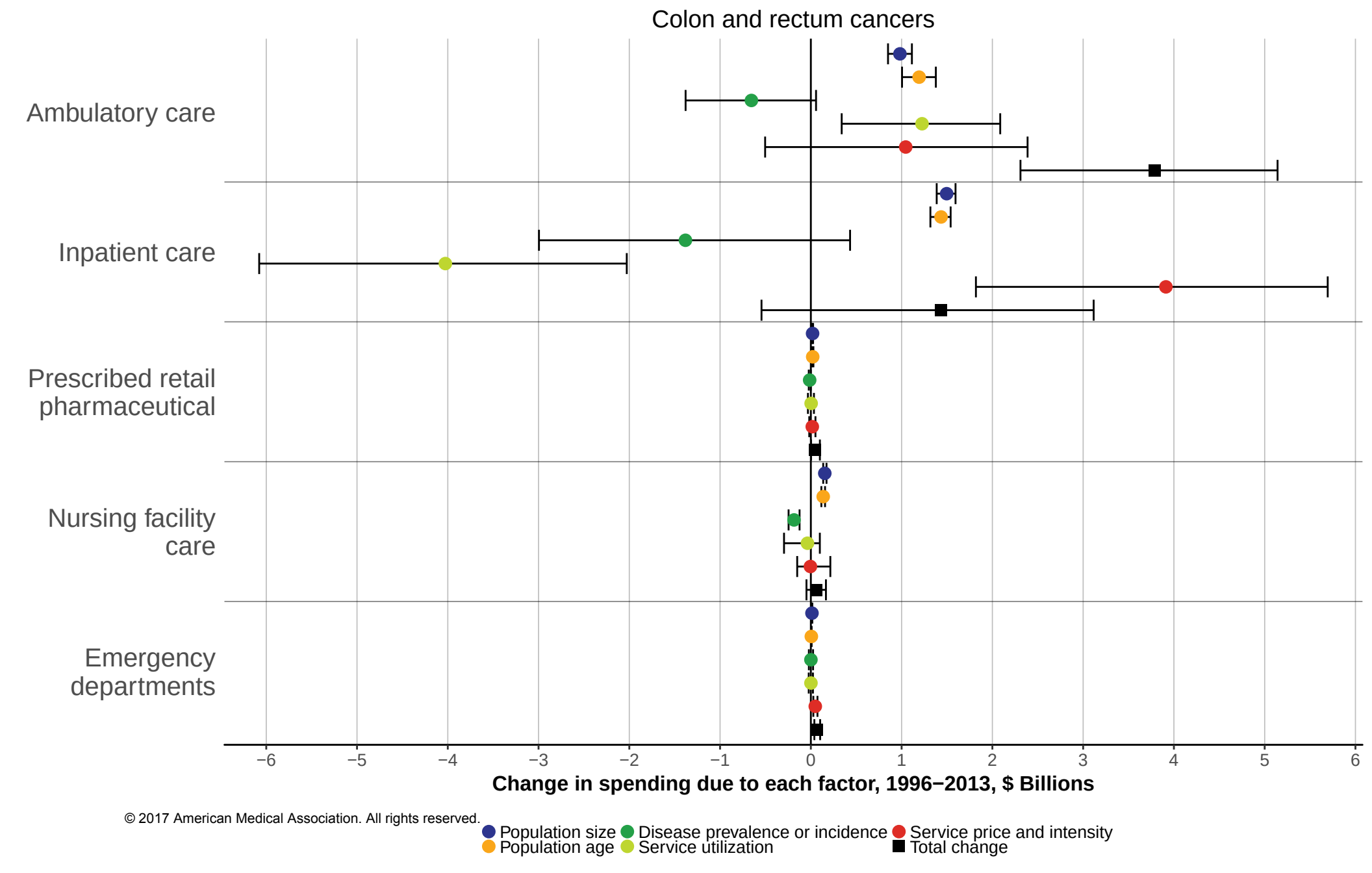












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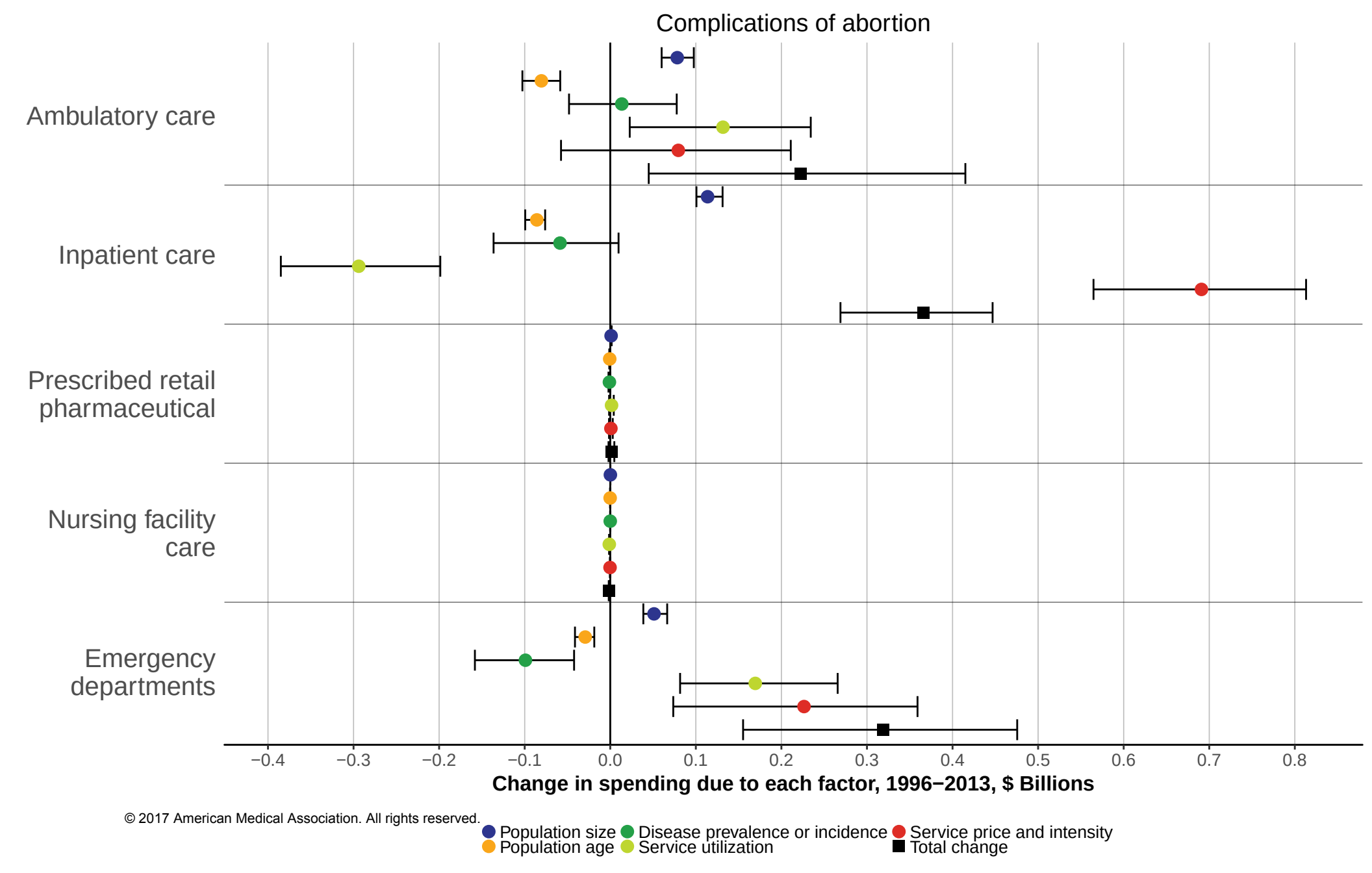

Population size
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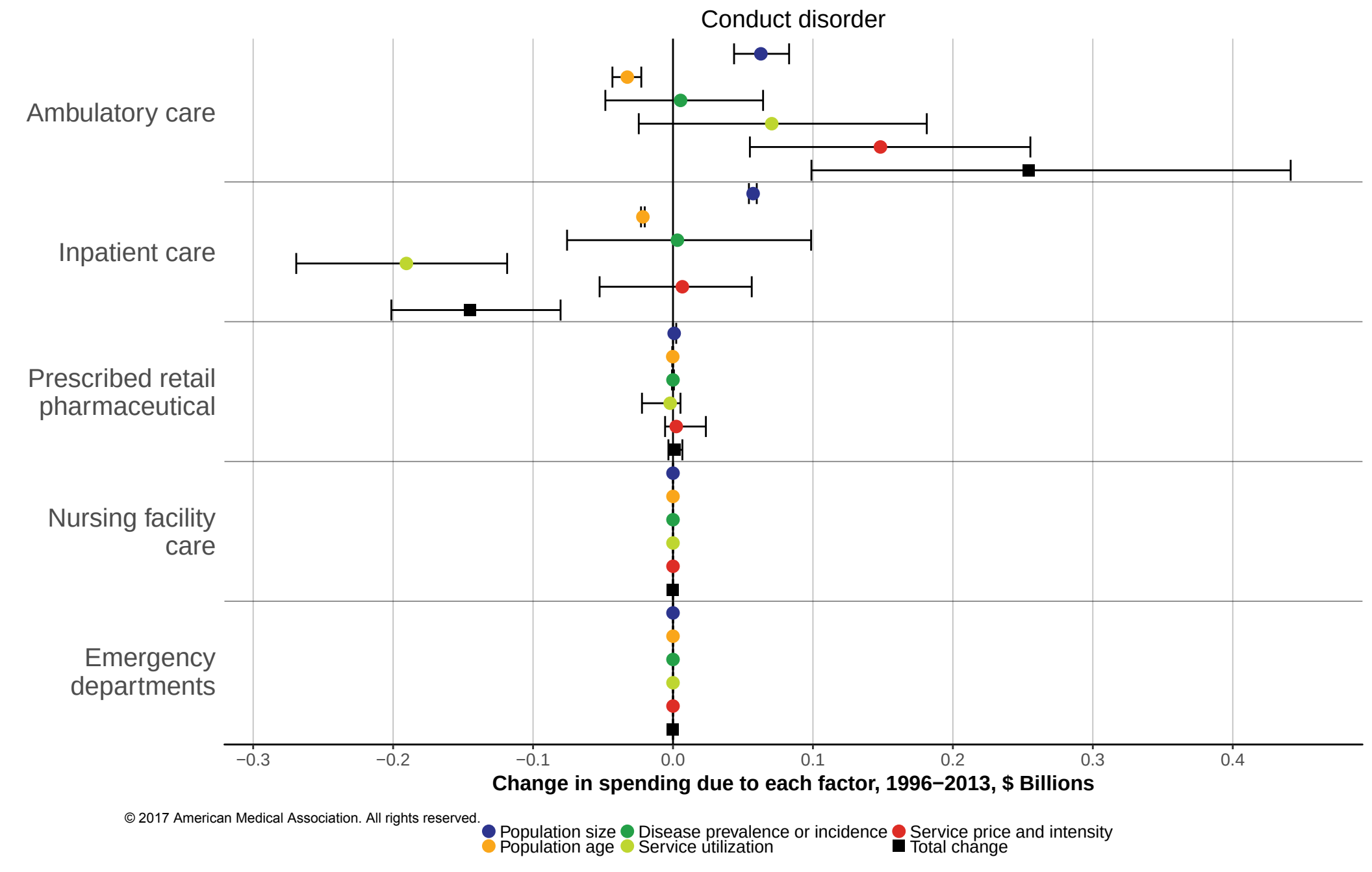

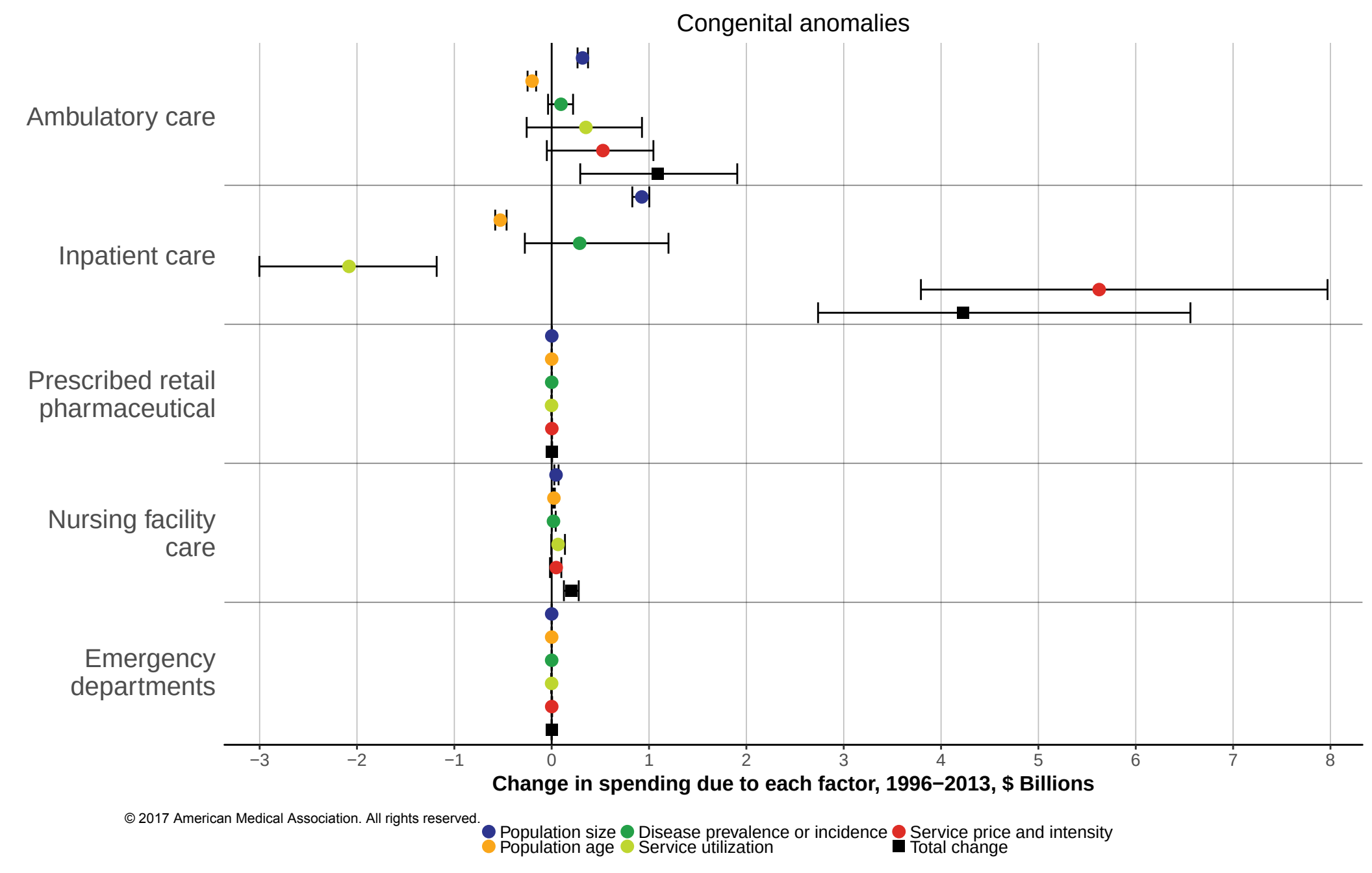

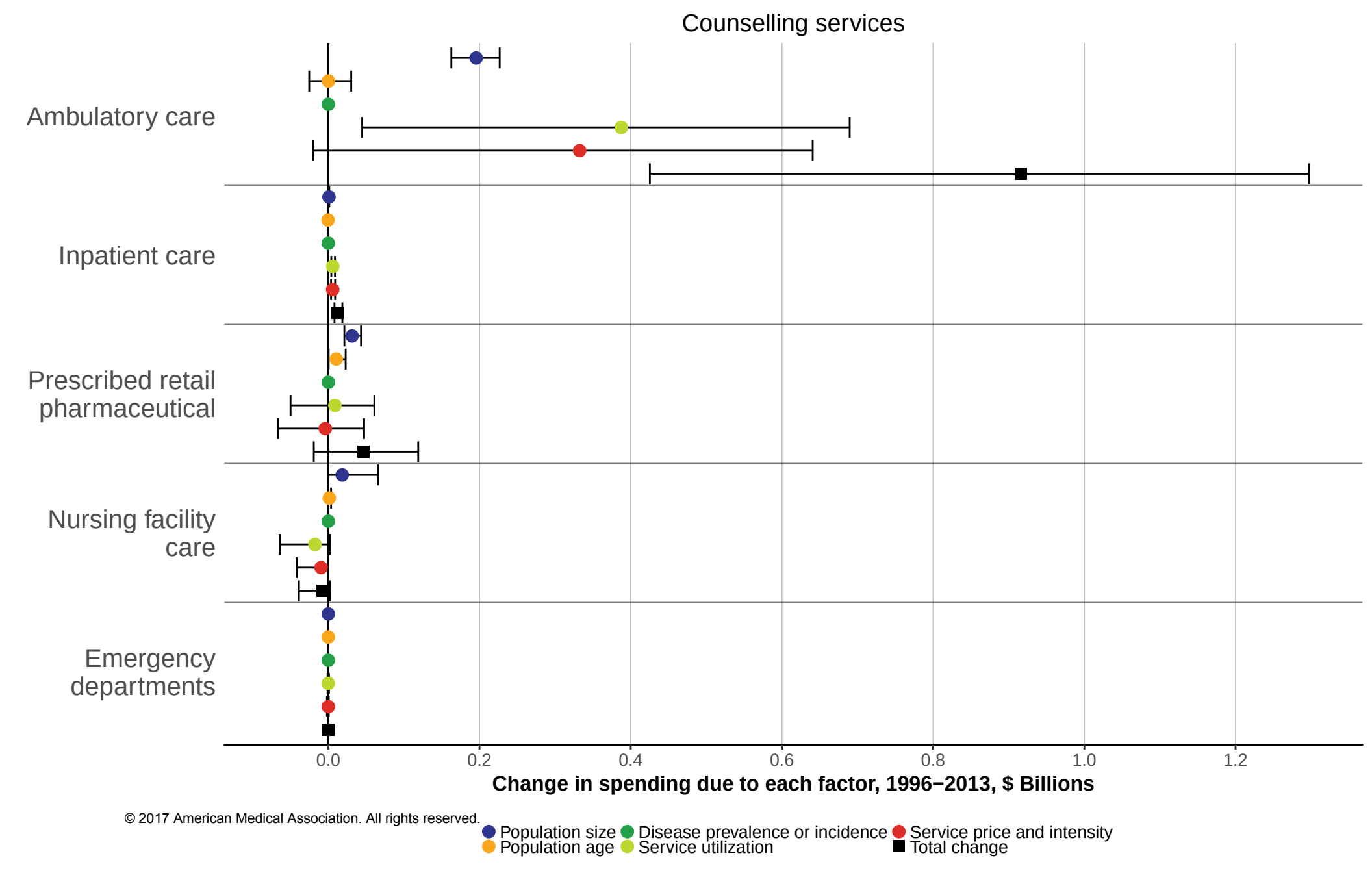

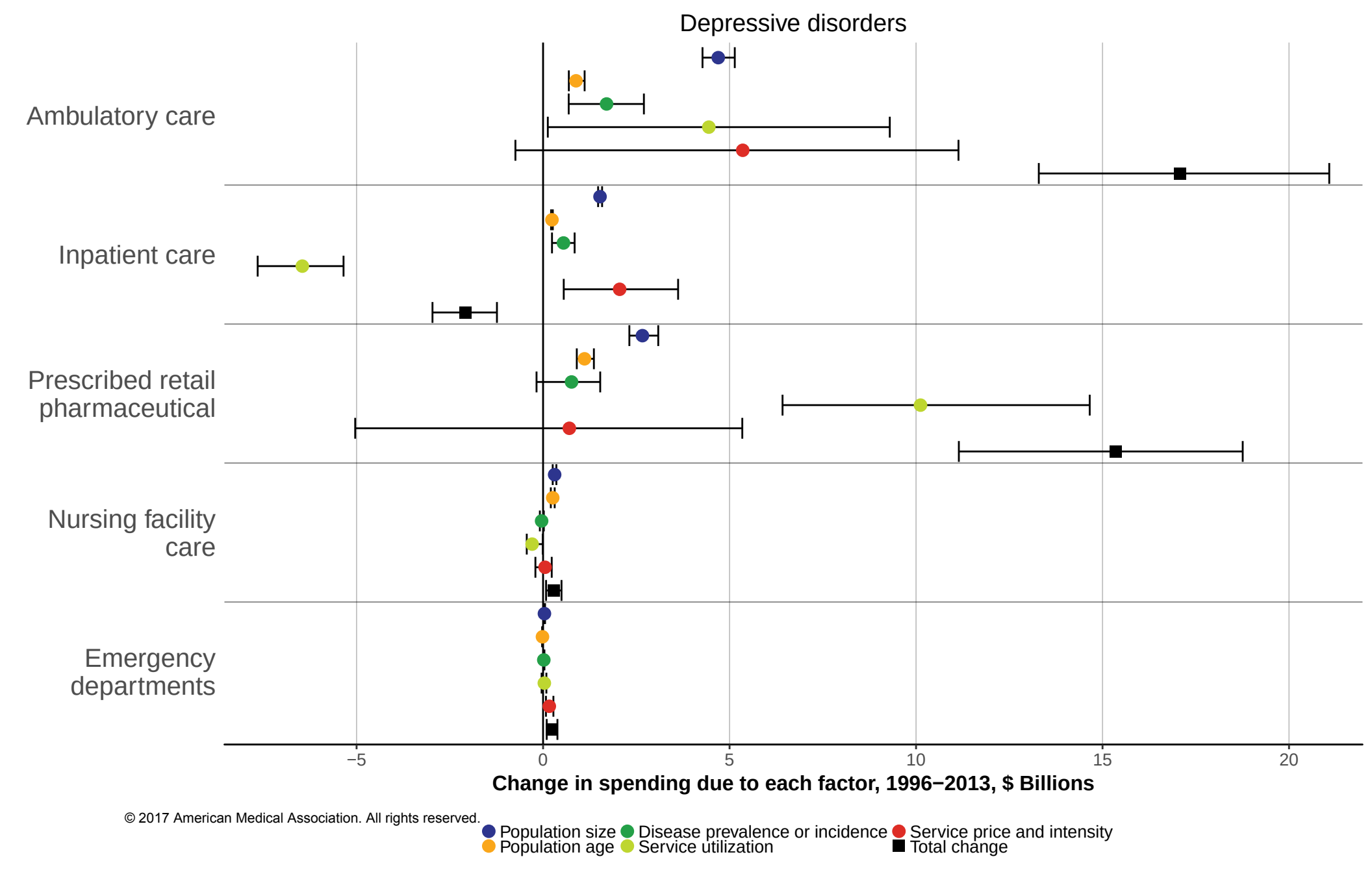

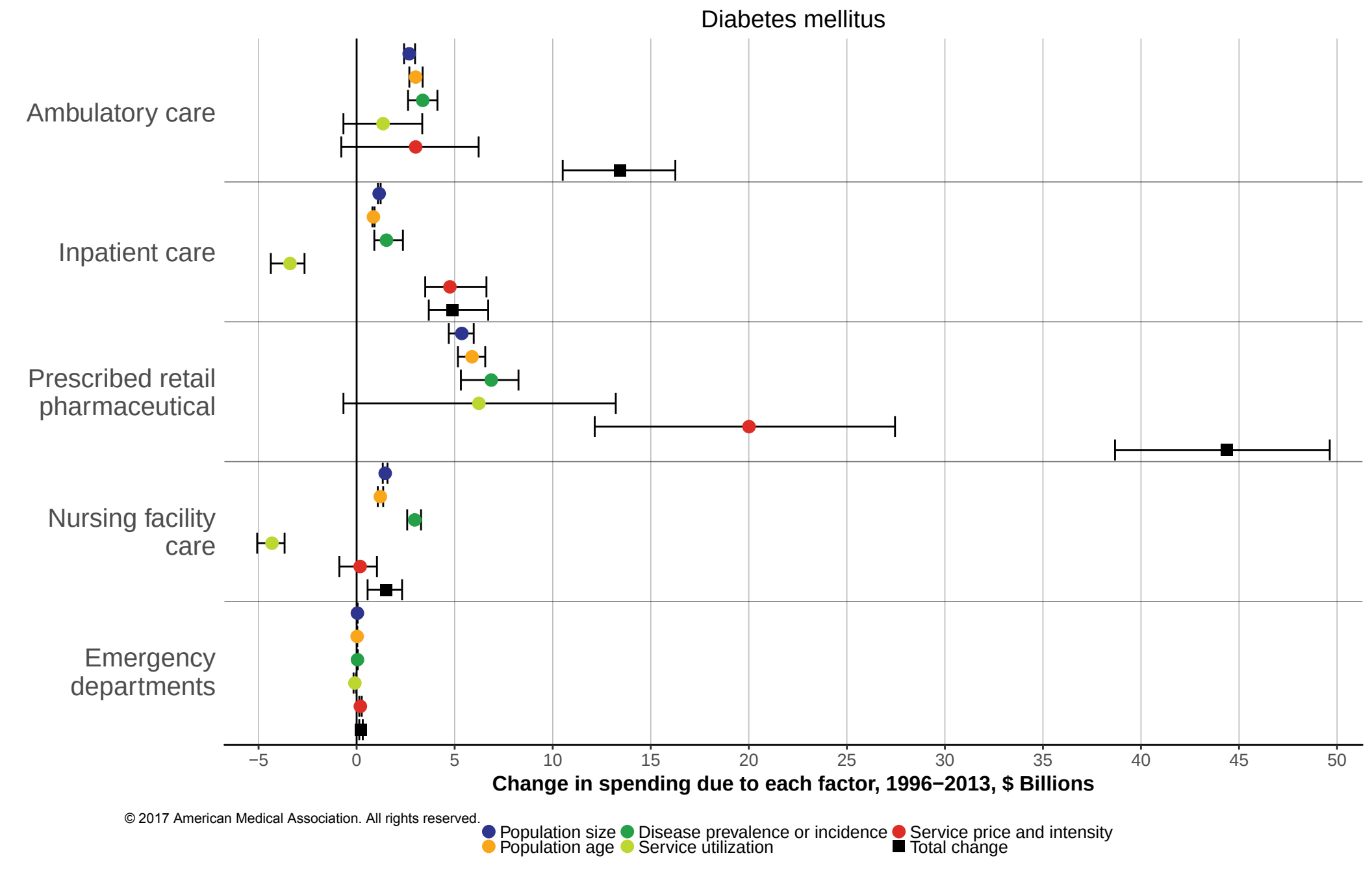

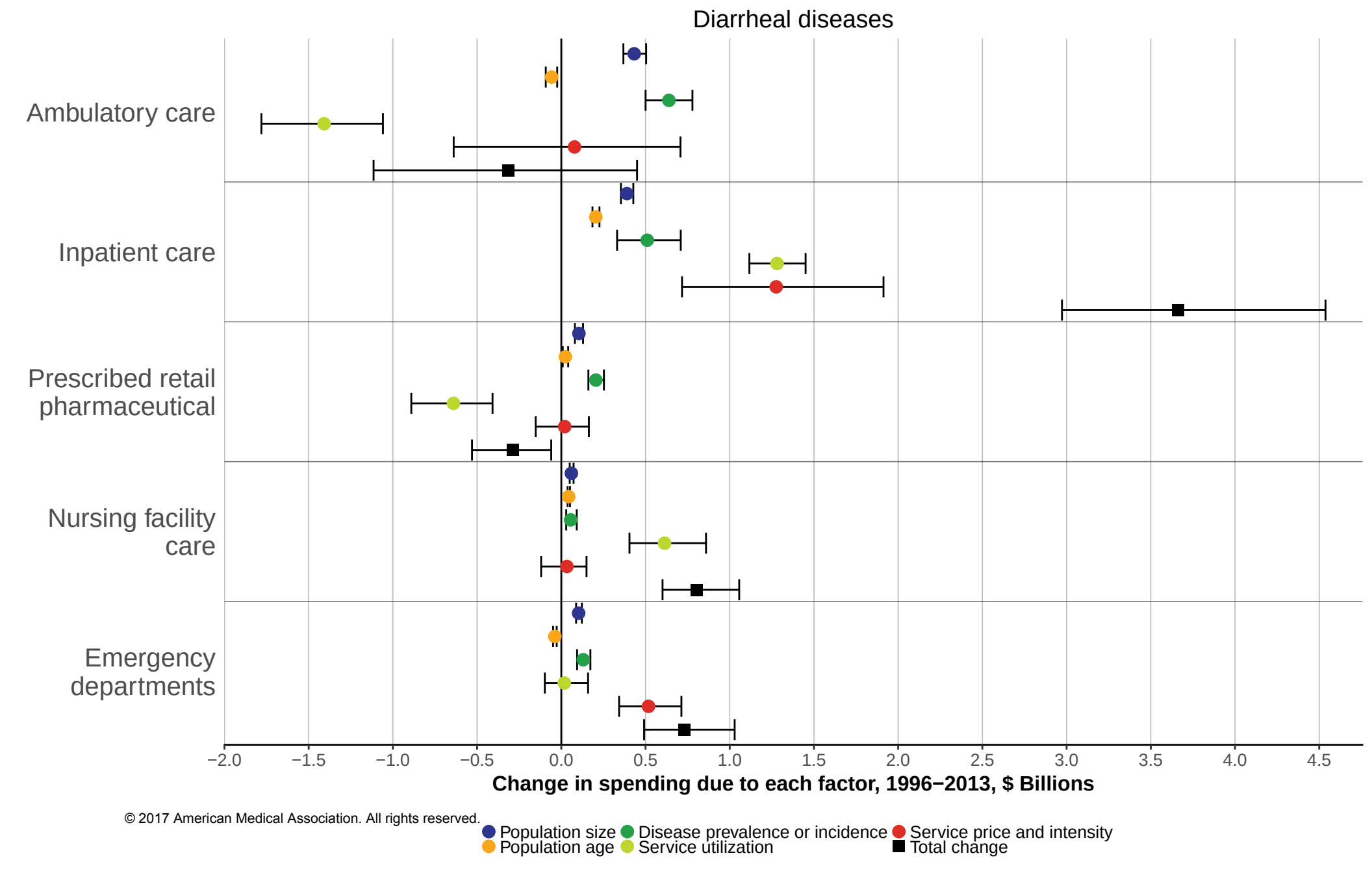
Diarrheal diseases
Ambulatory care
Inpatient care
Prescribed retail pharmaceutical
Nursing facility care
Emergency departments
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
Change in spending due to each factor, 1996−2013, $ Billions
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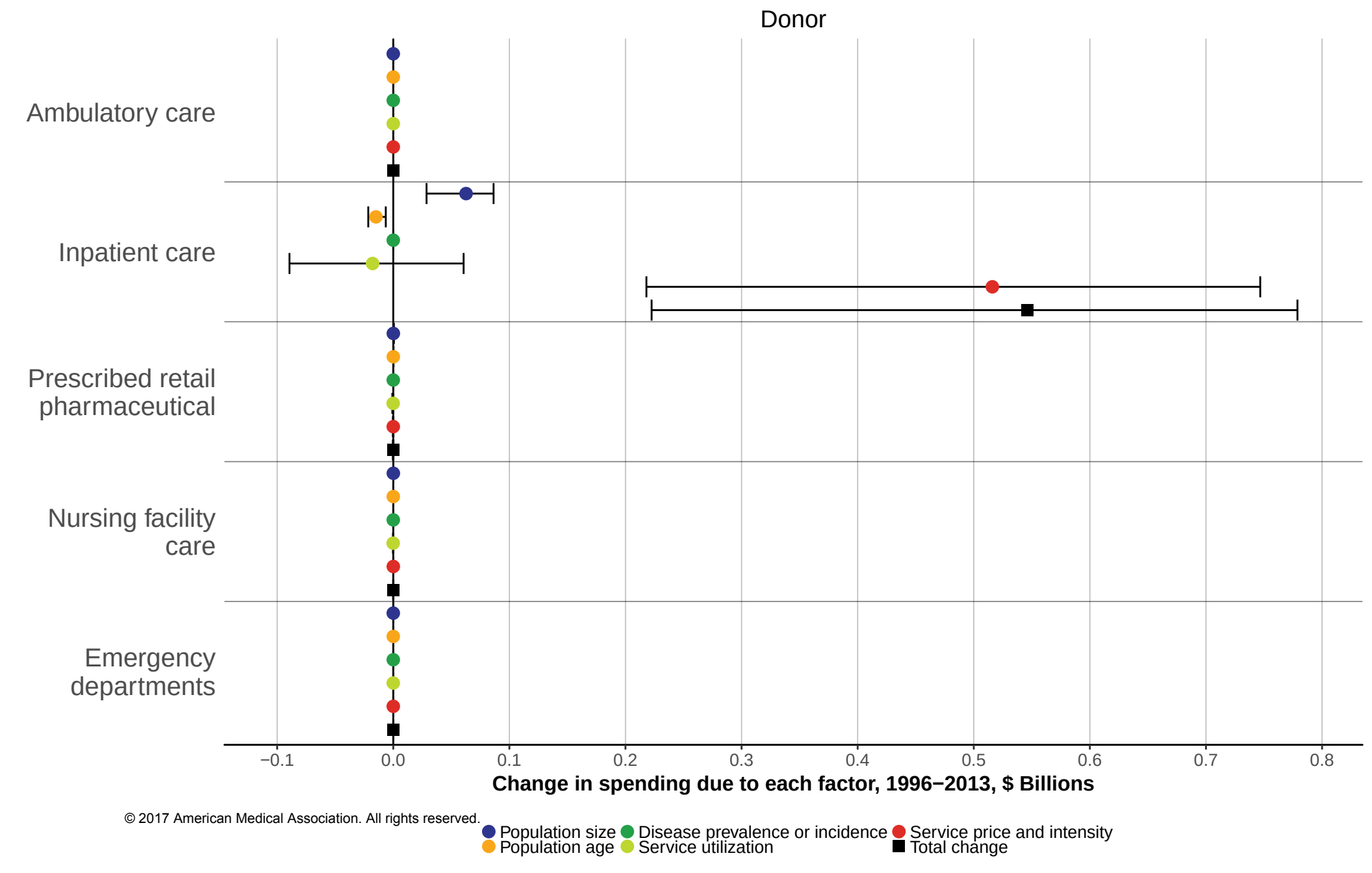
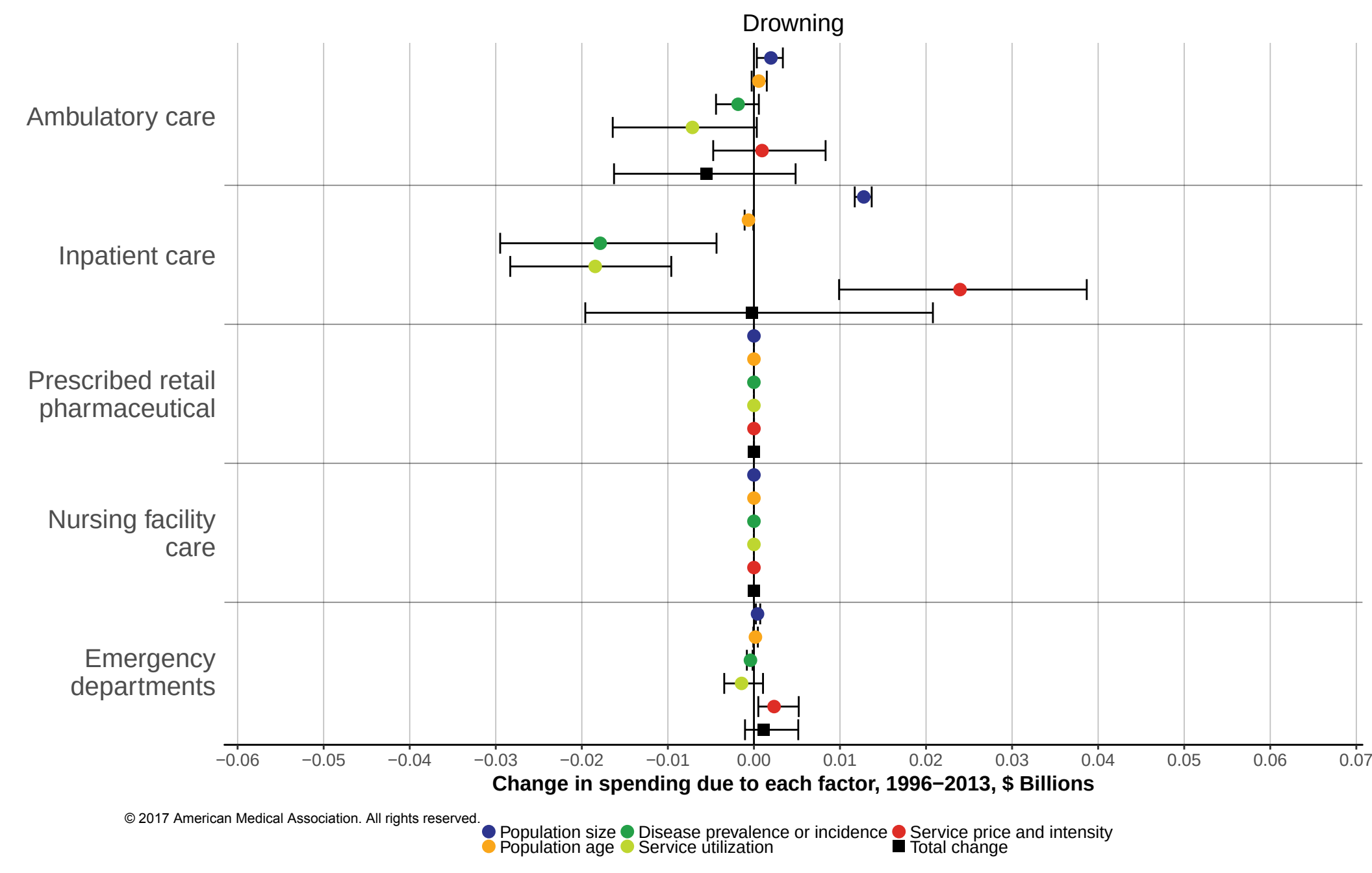
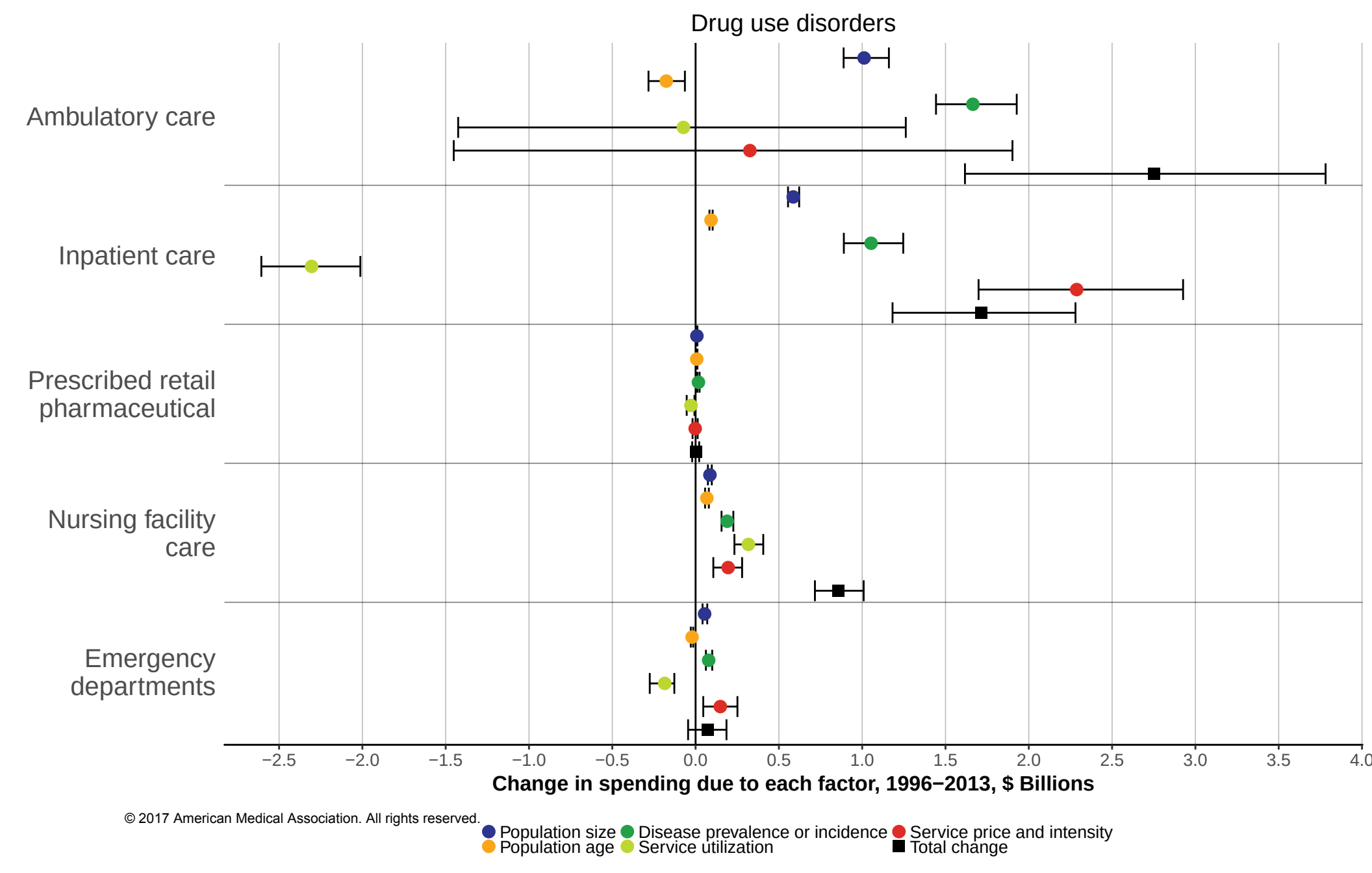
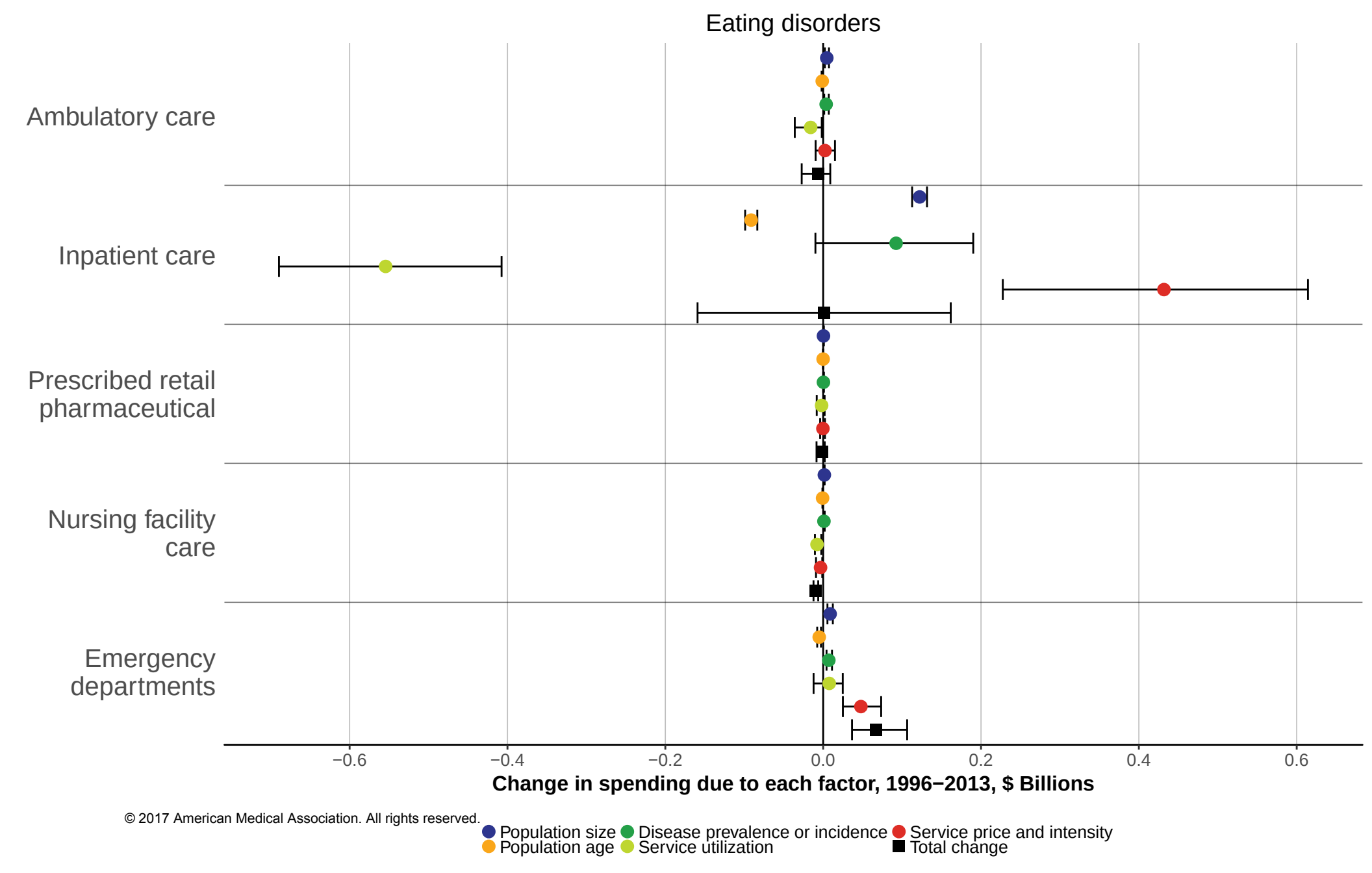
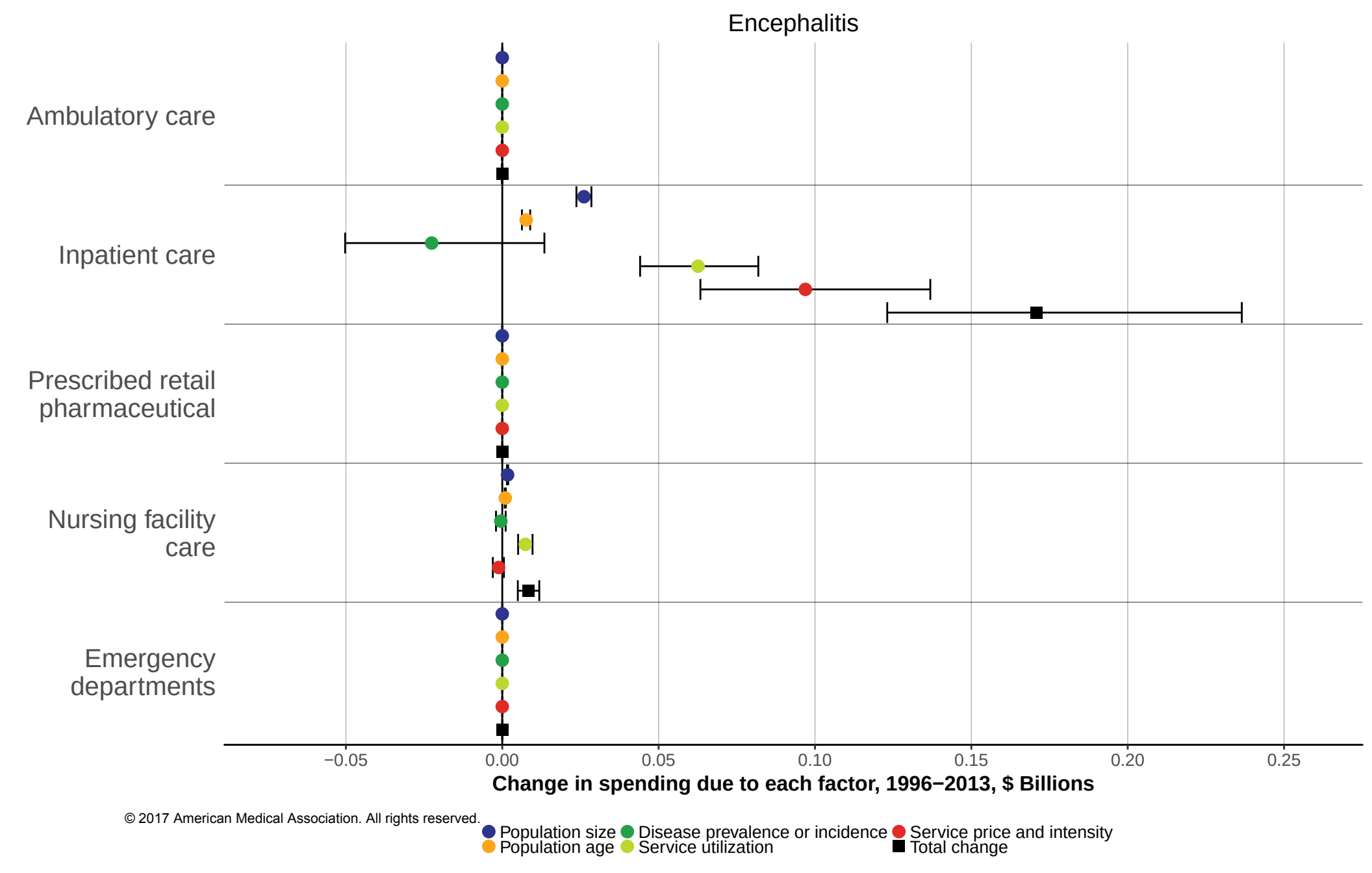
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

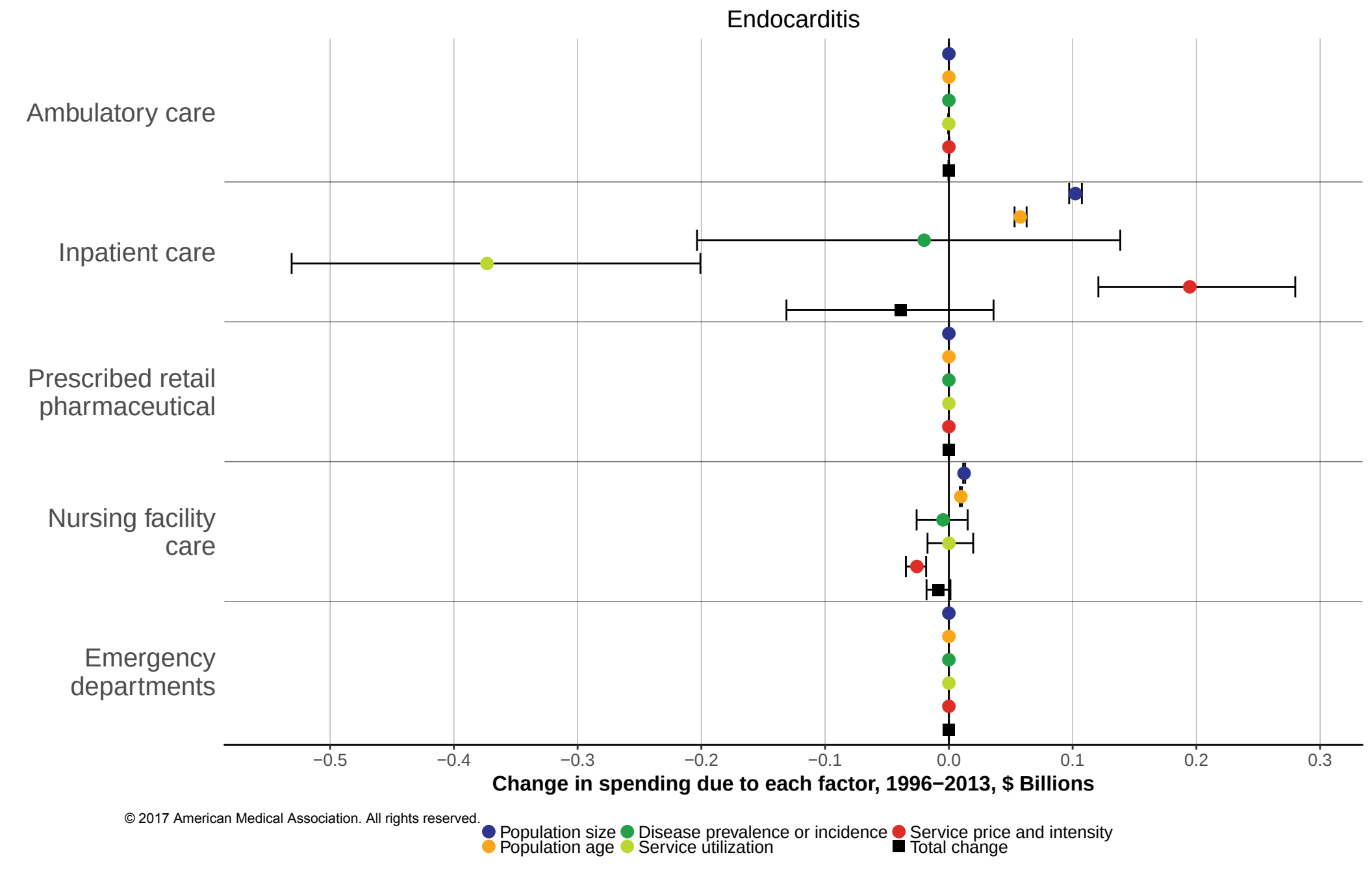


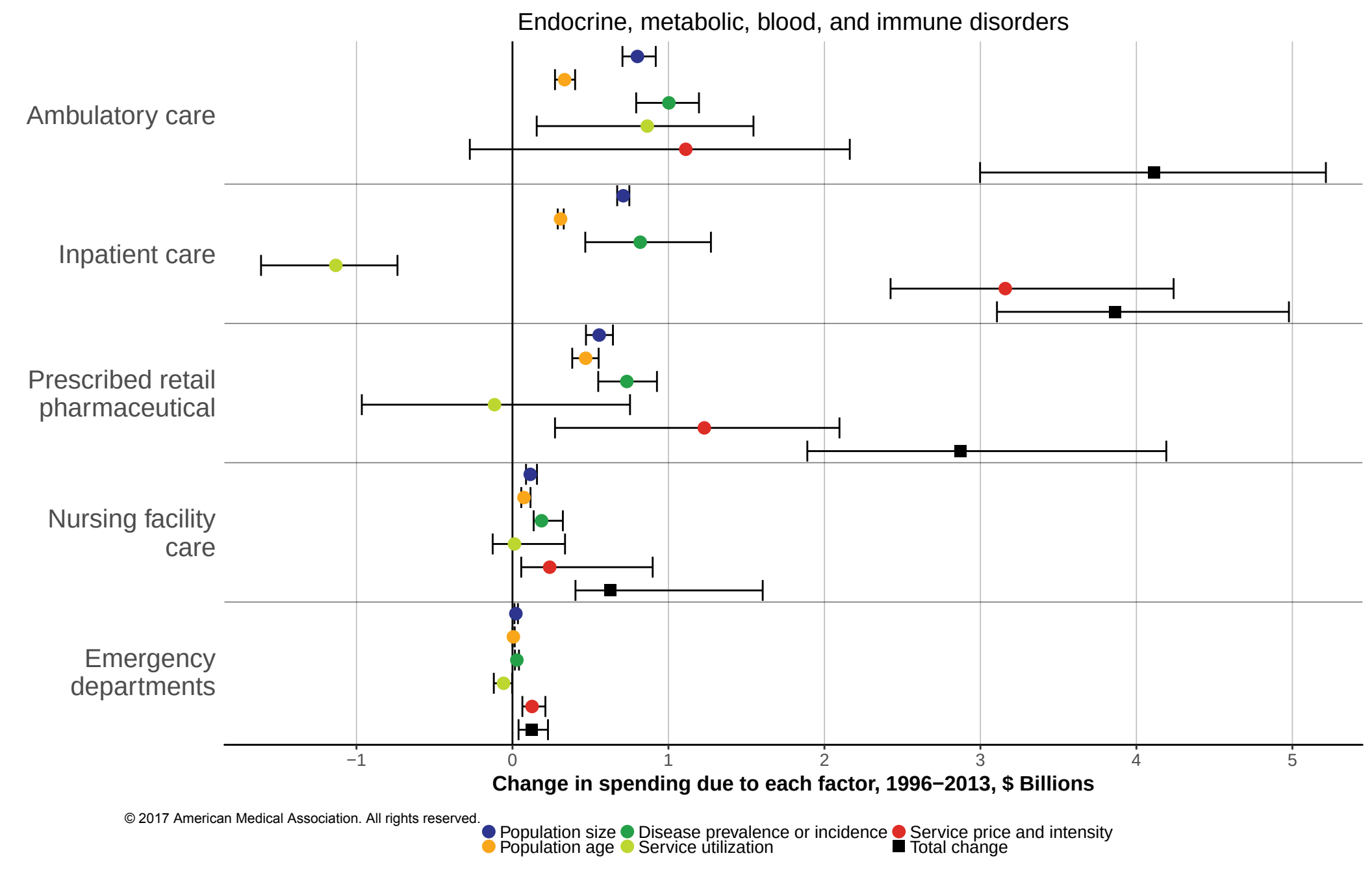


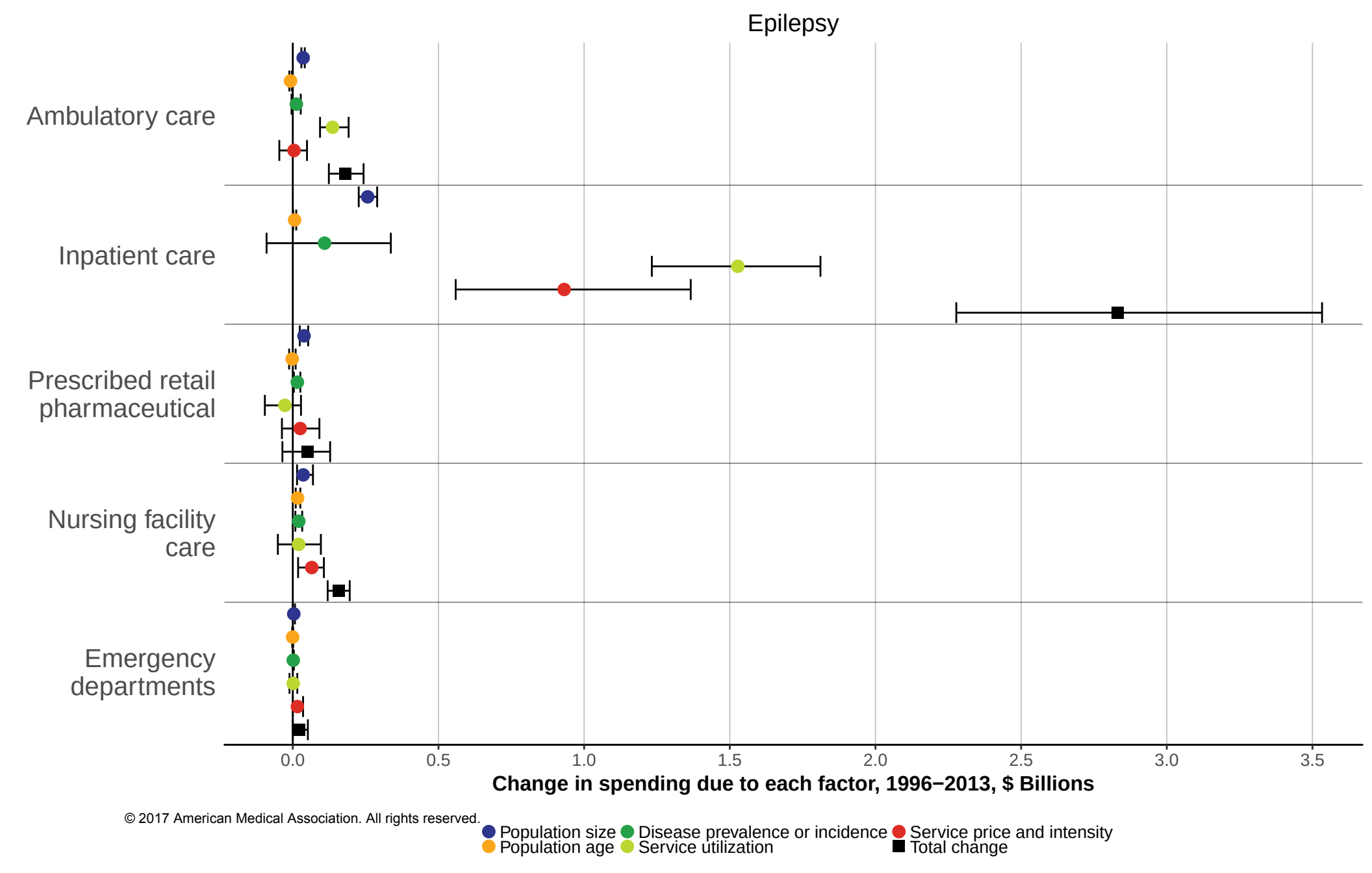


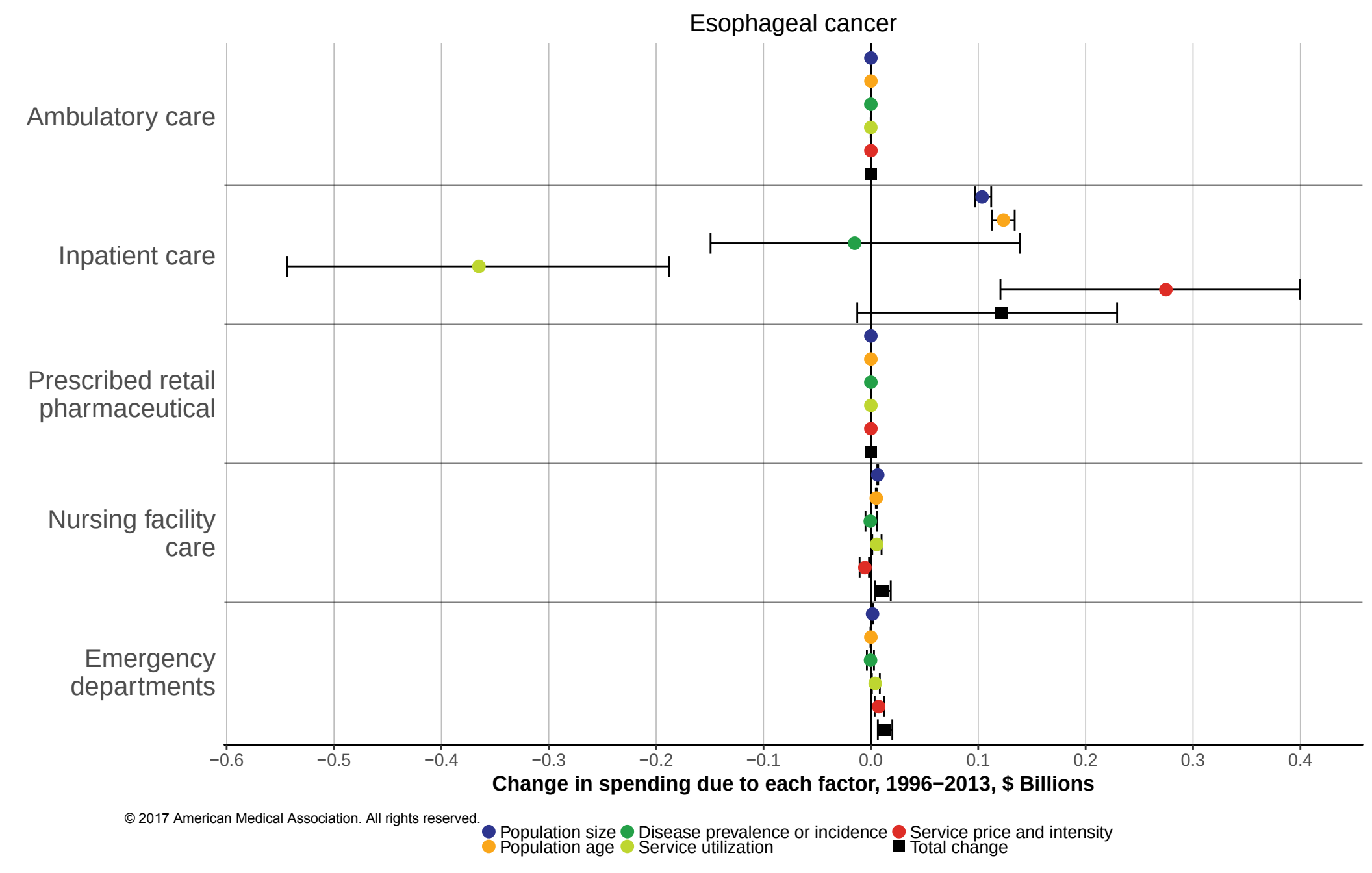


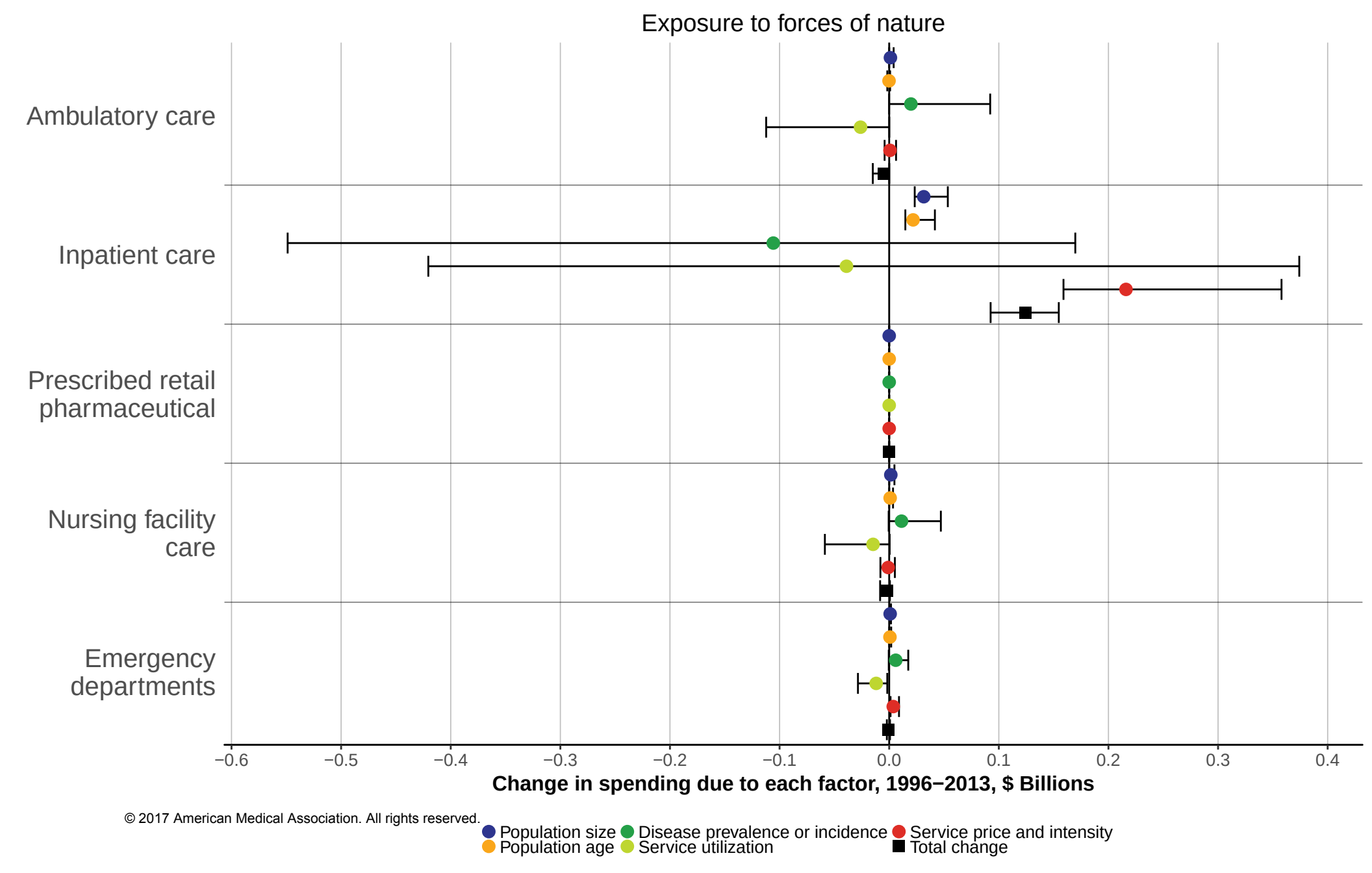


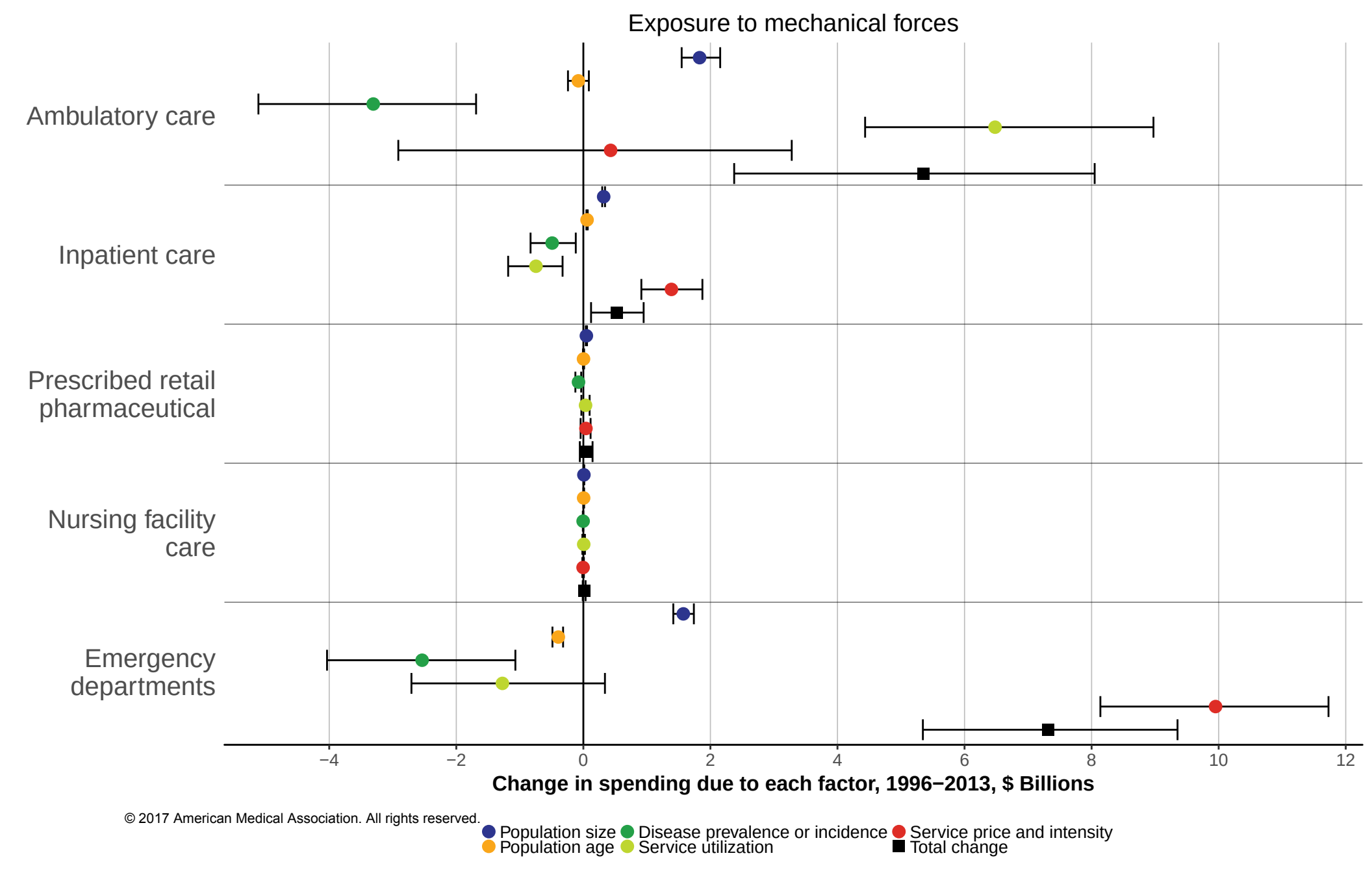


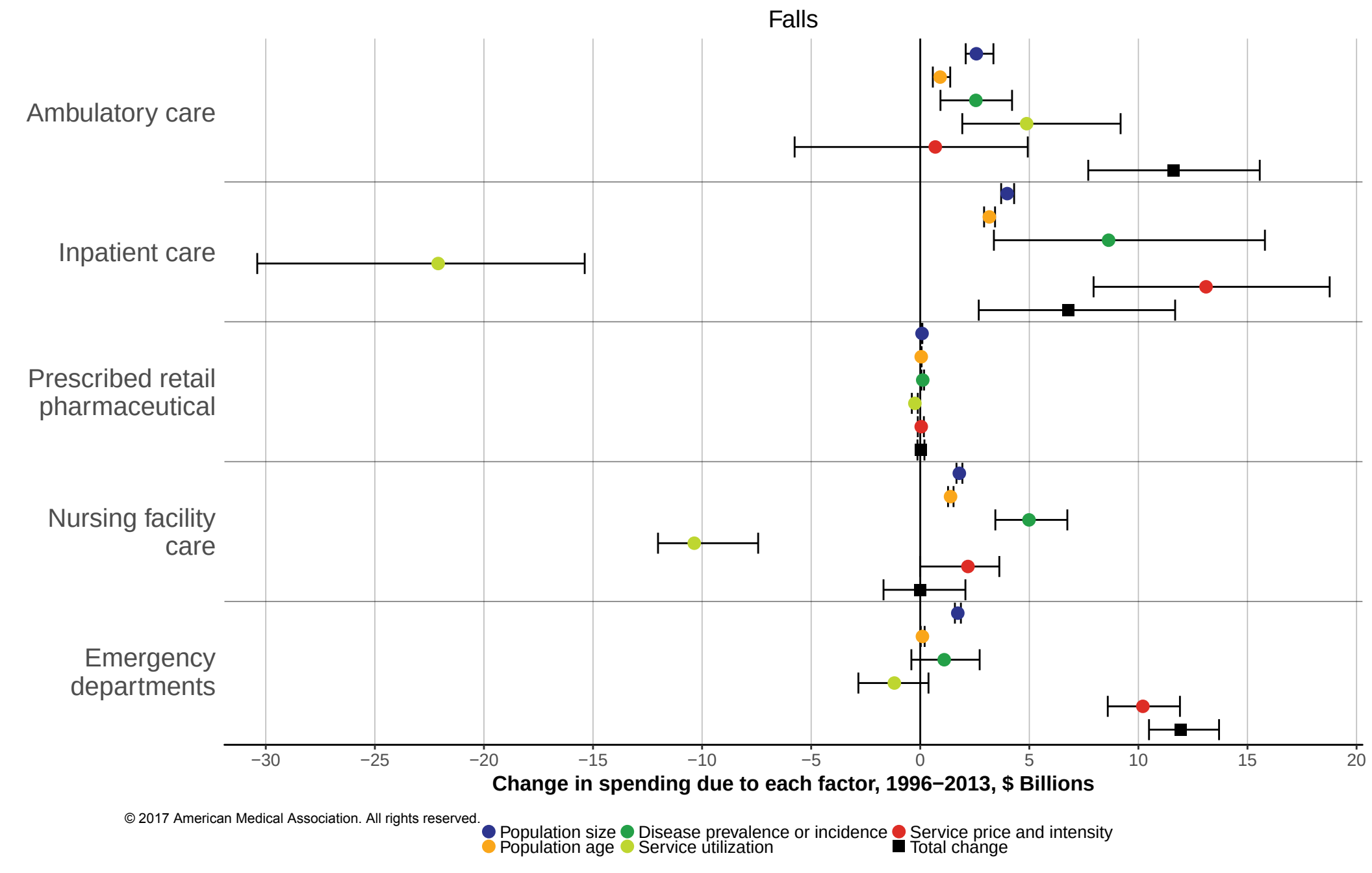


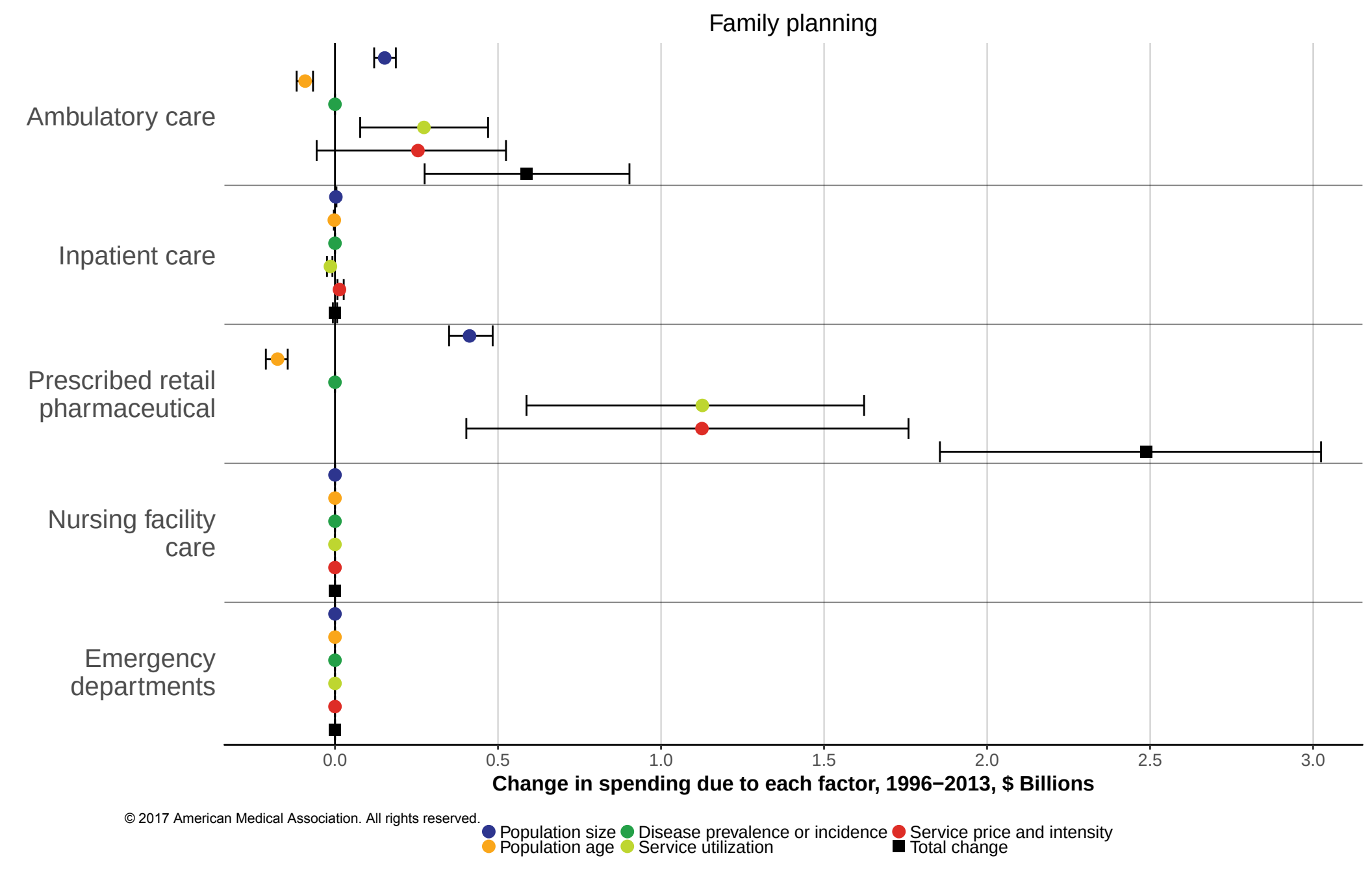


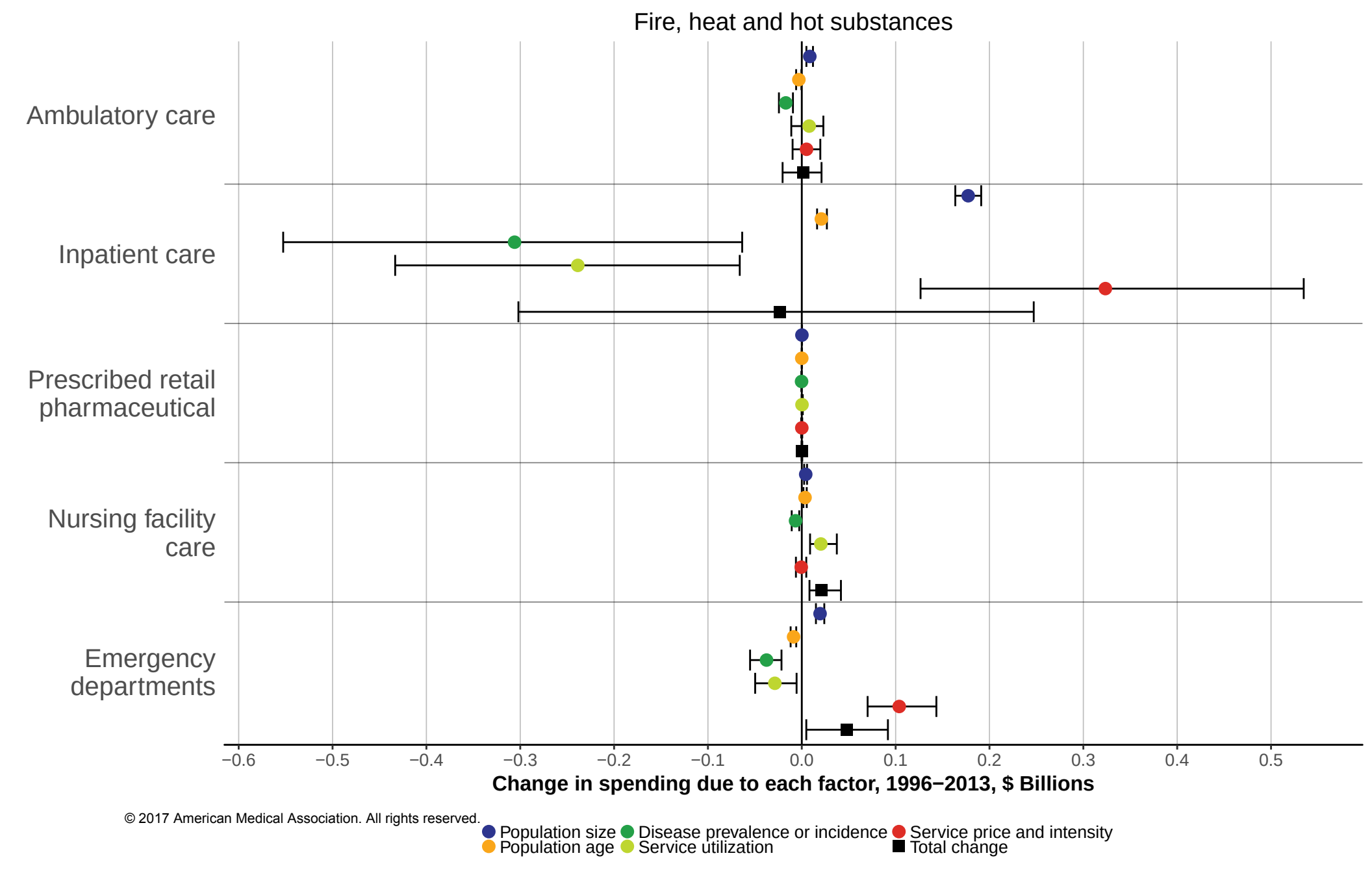


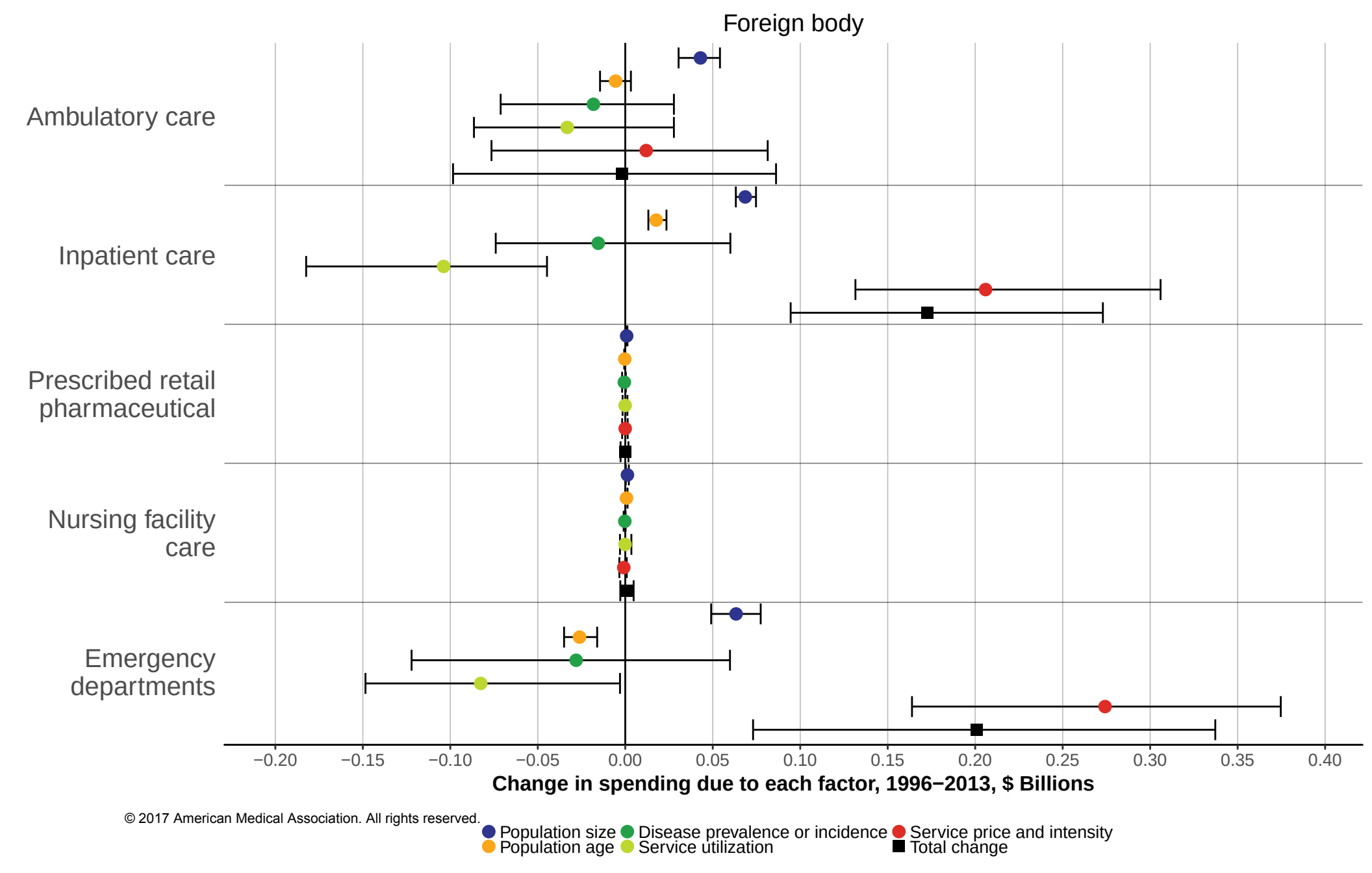


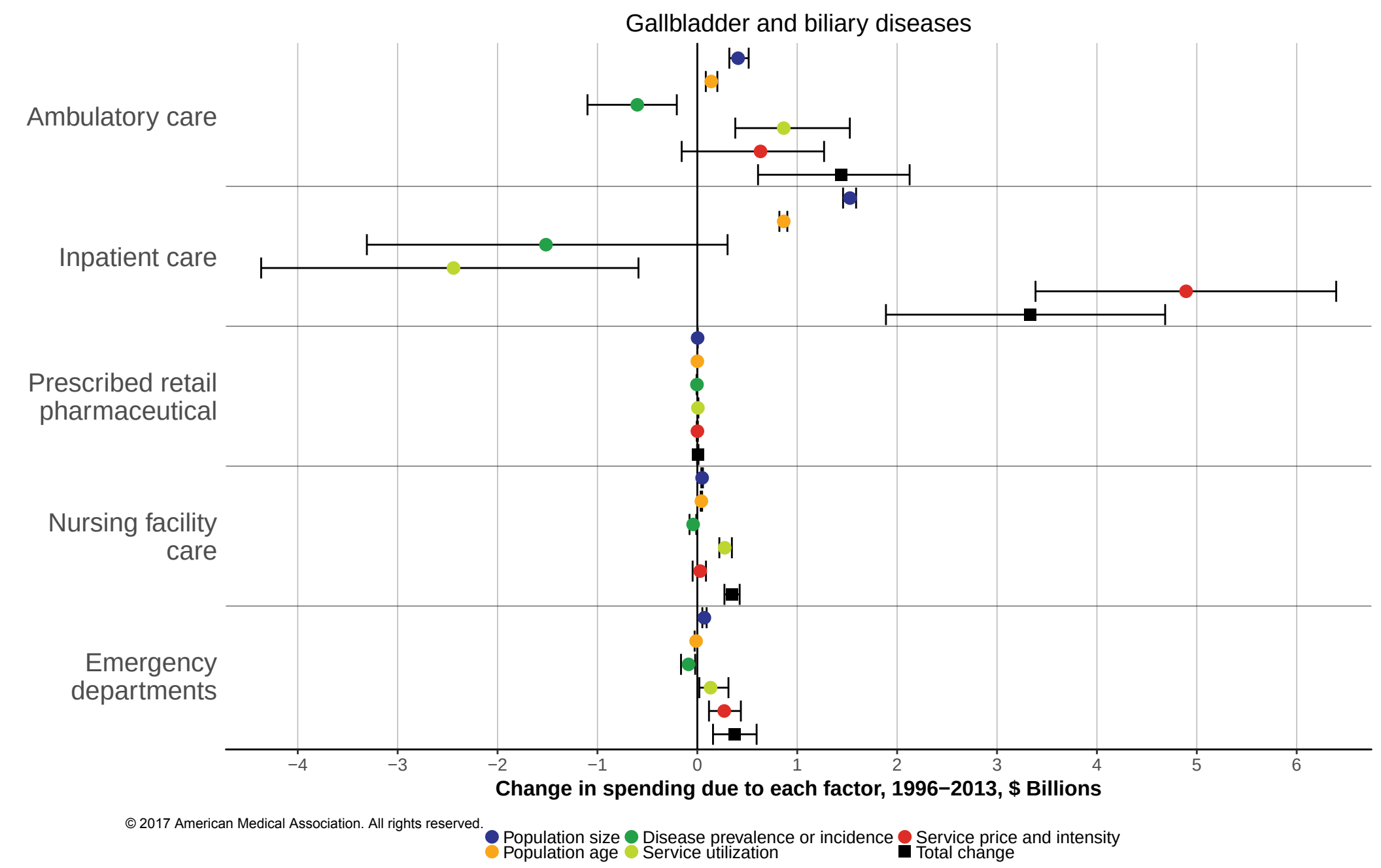


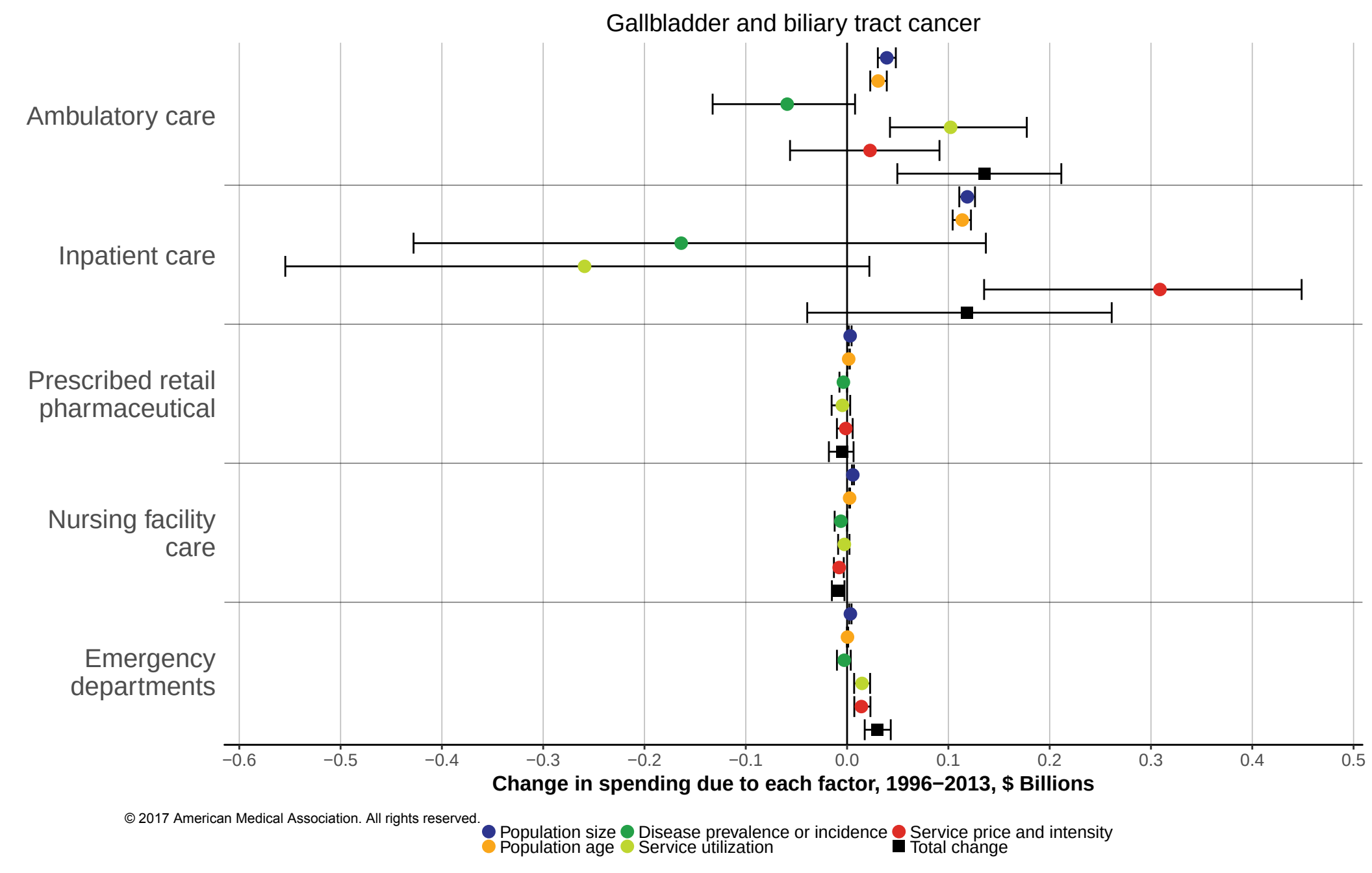


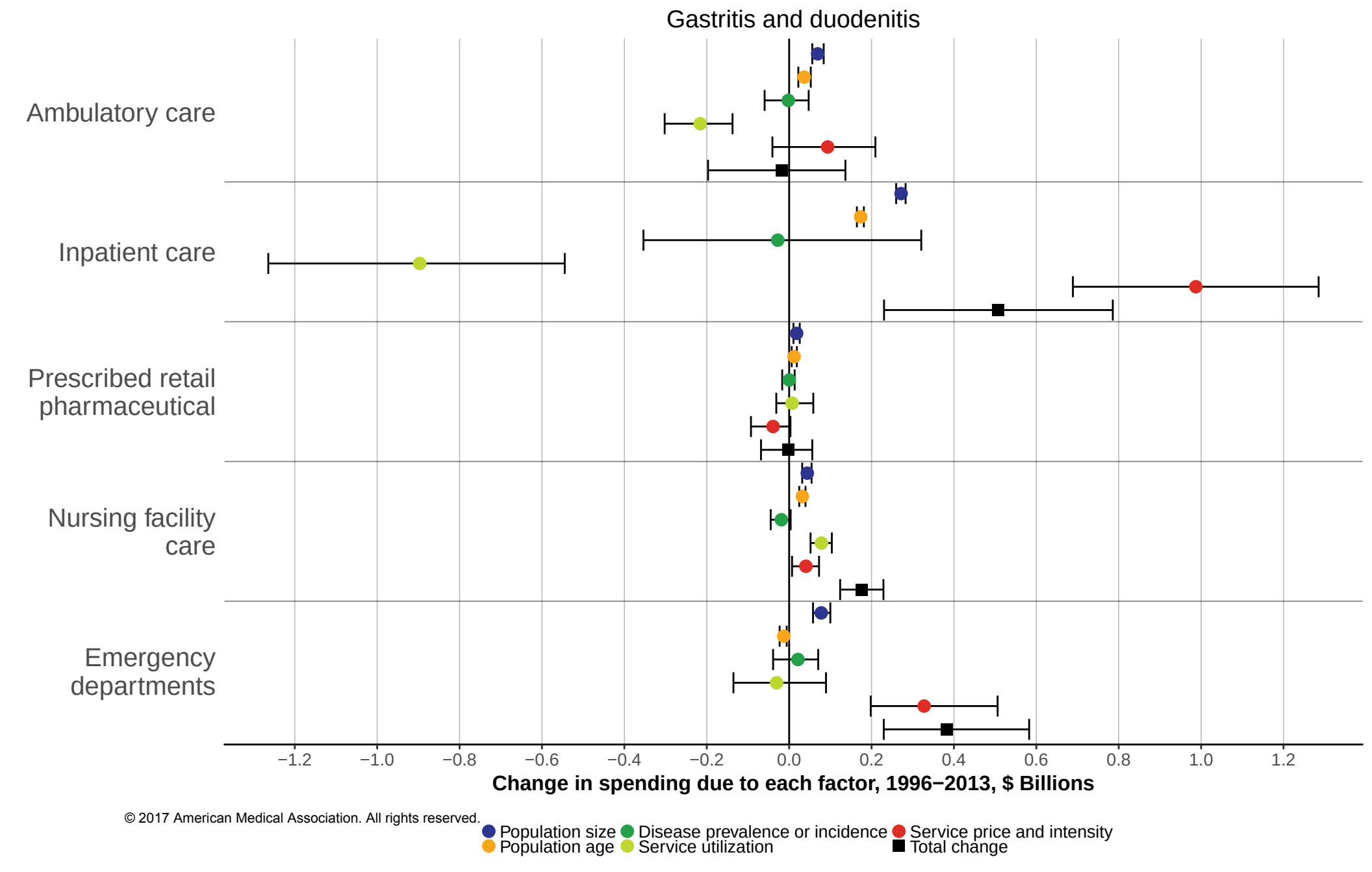


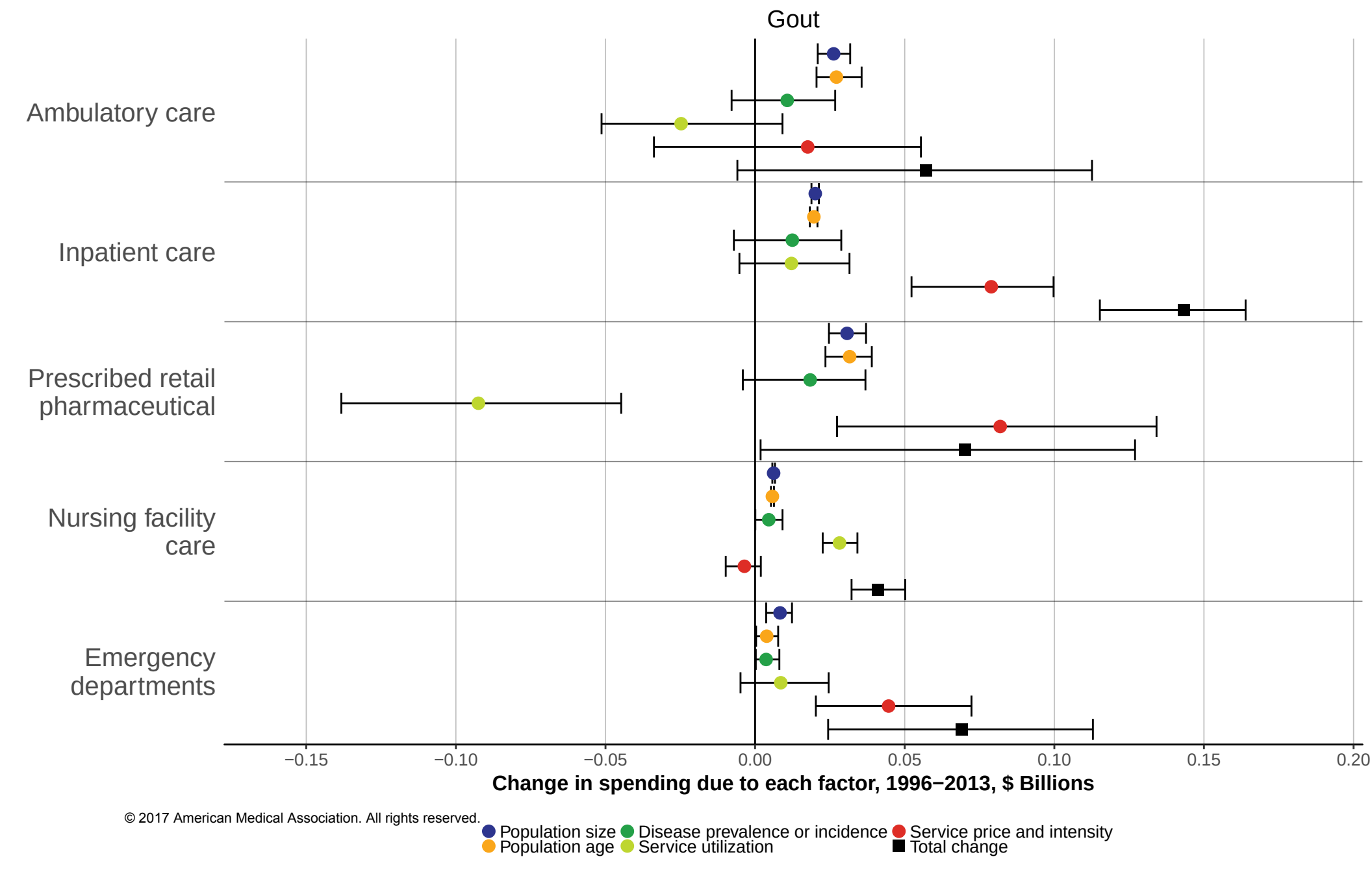


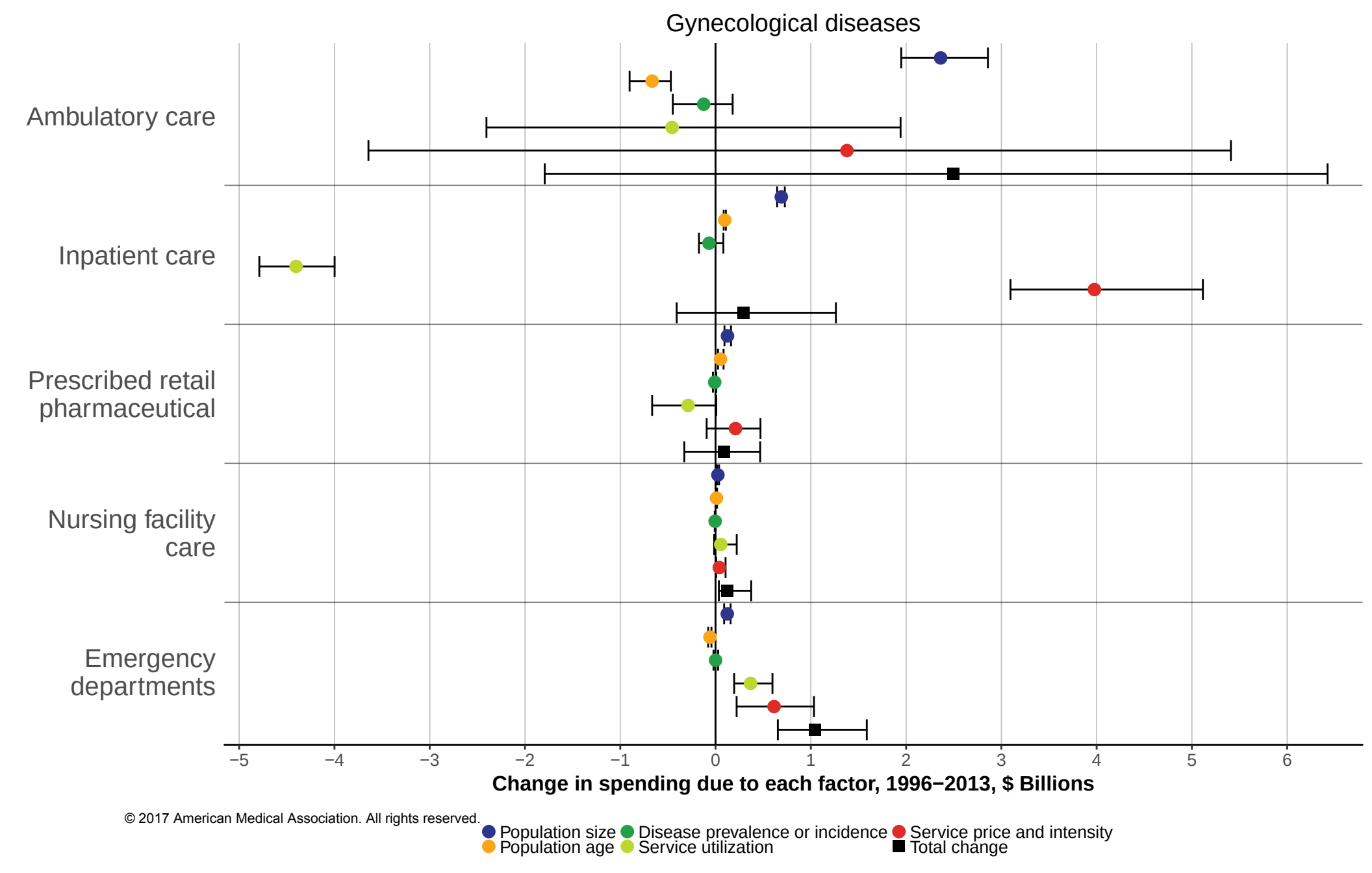




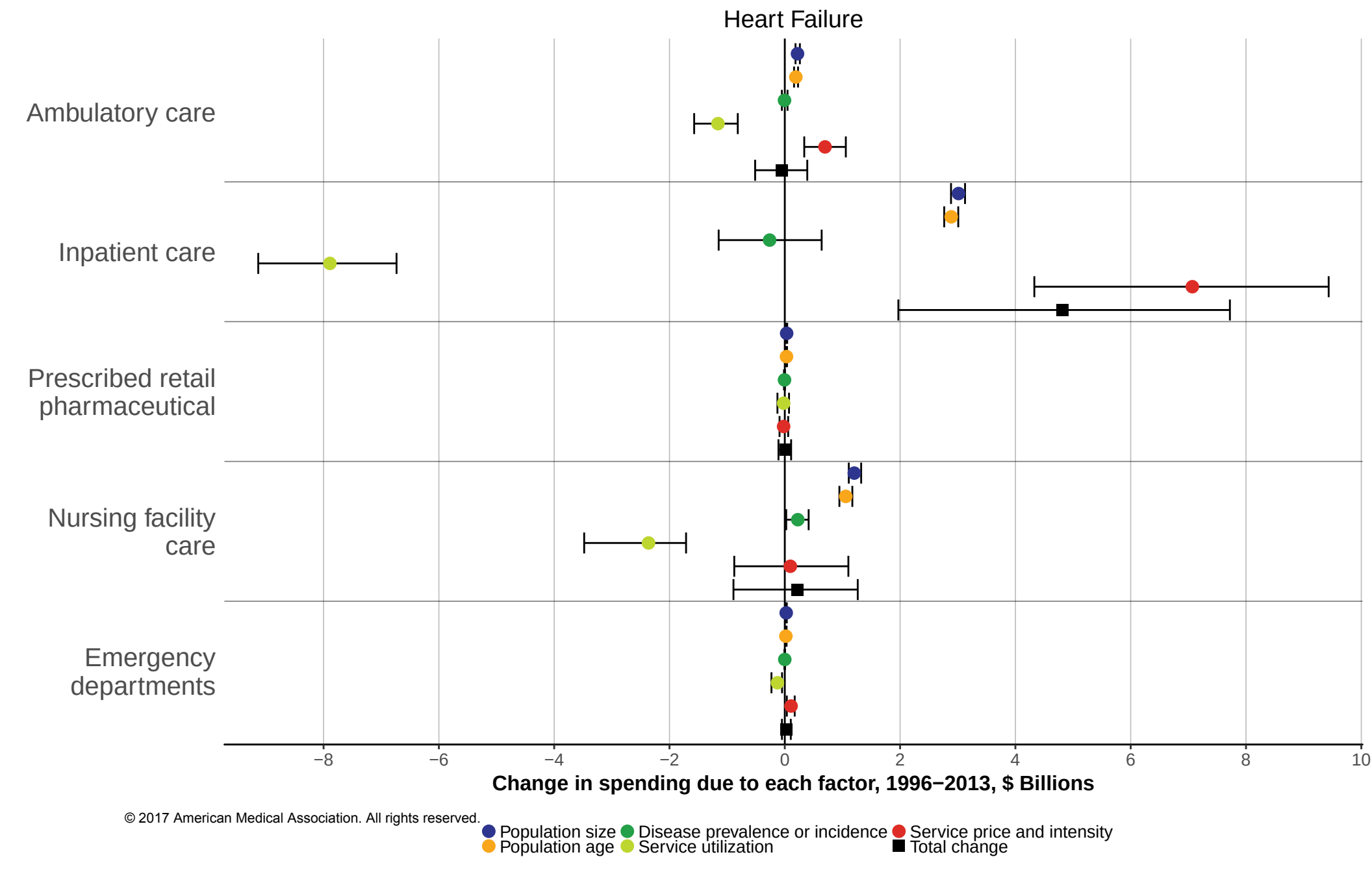


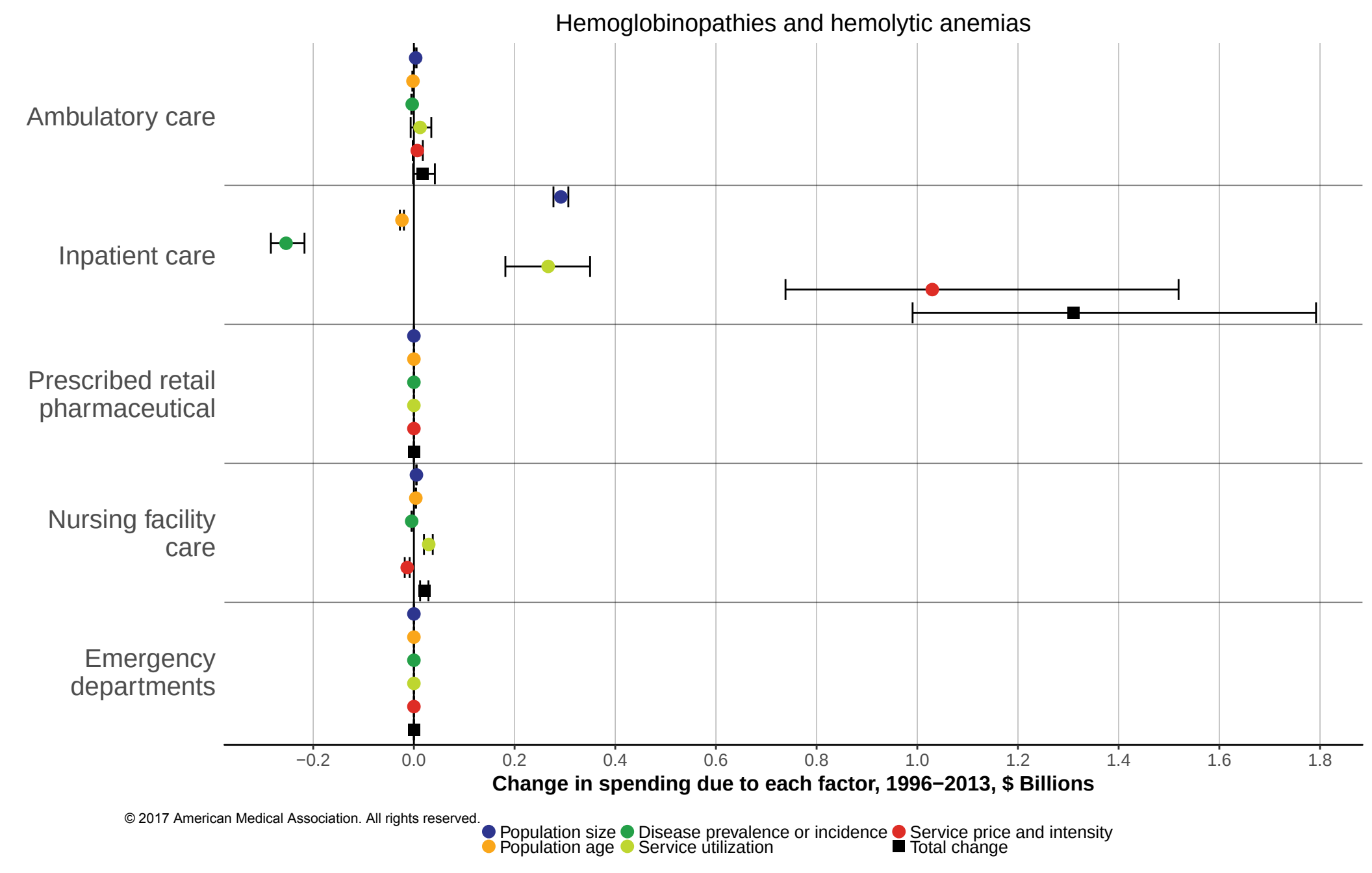


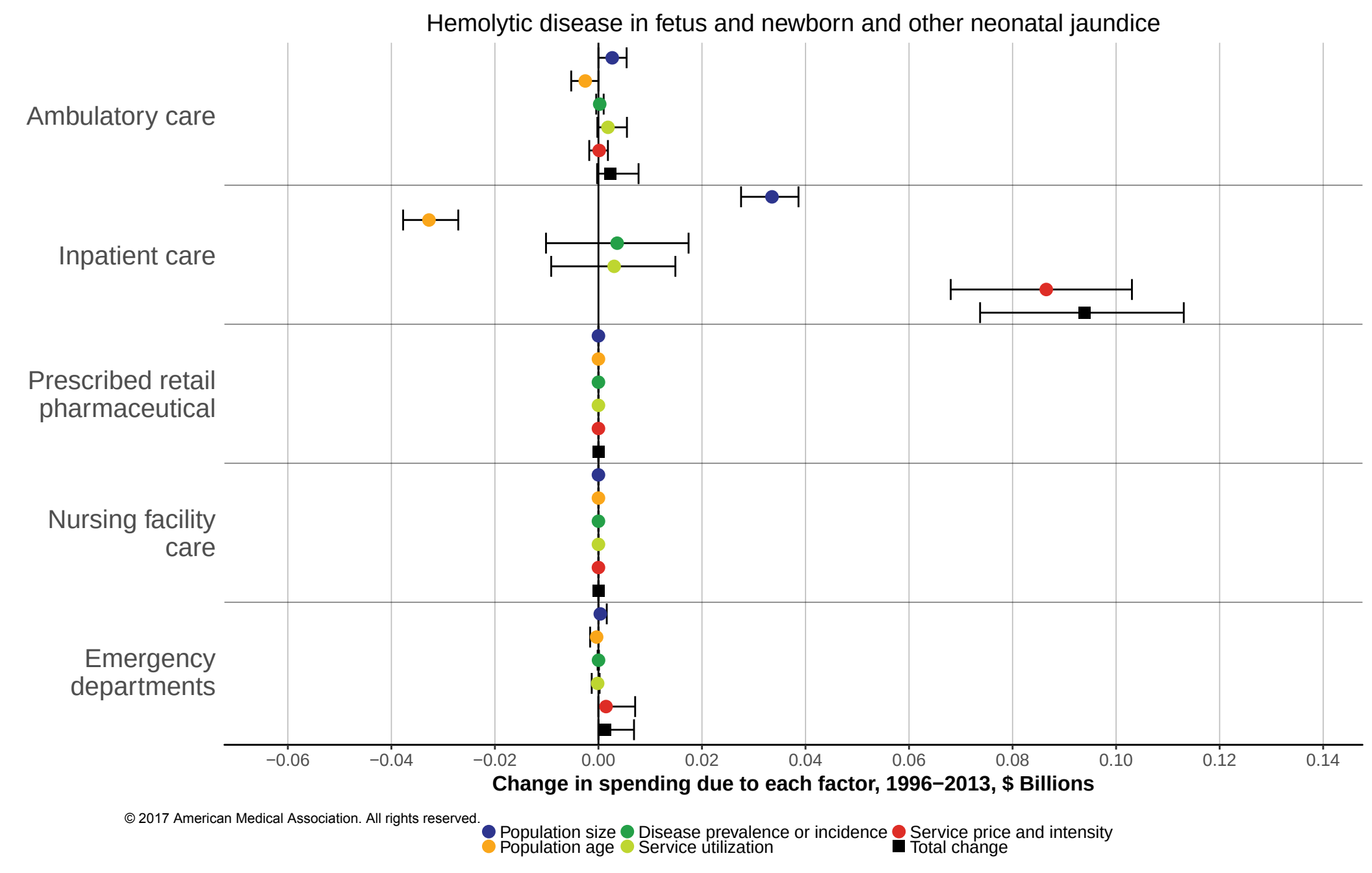


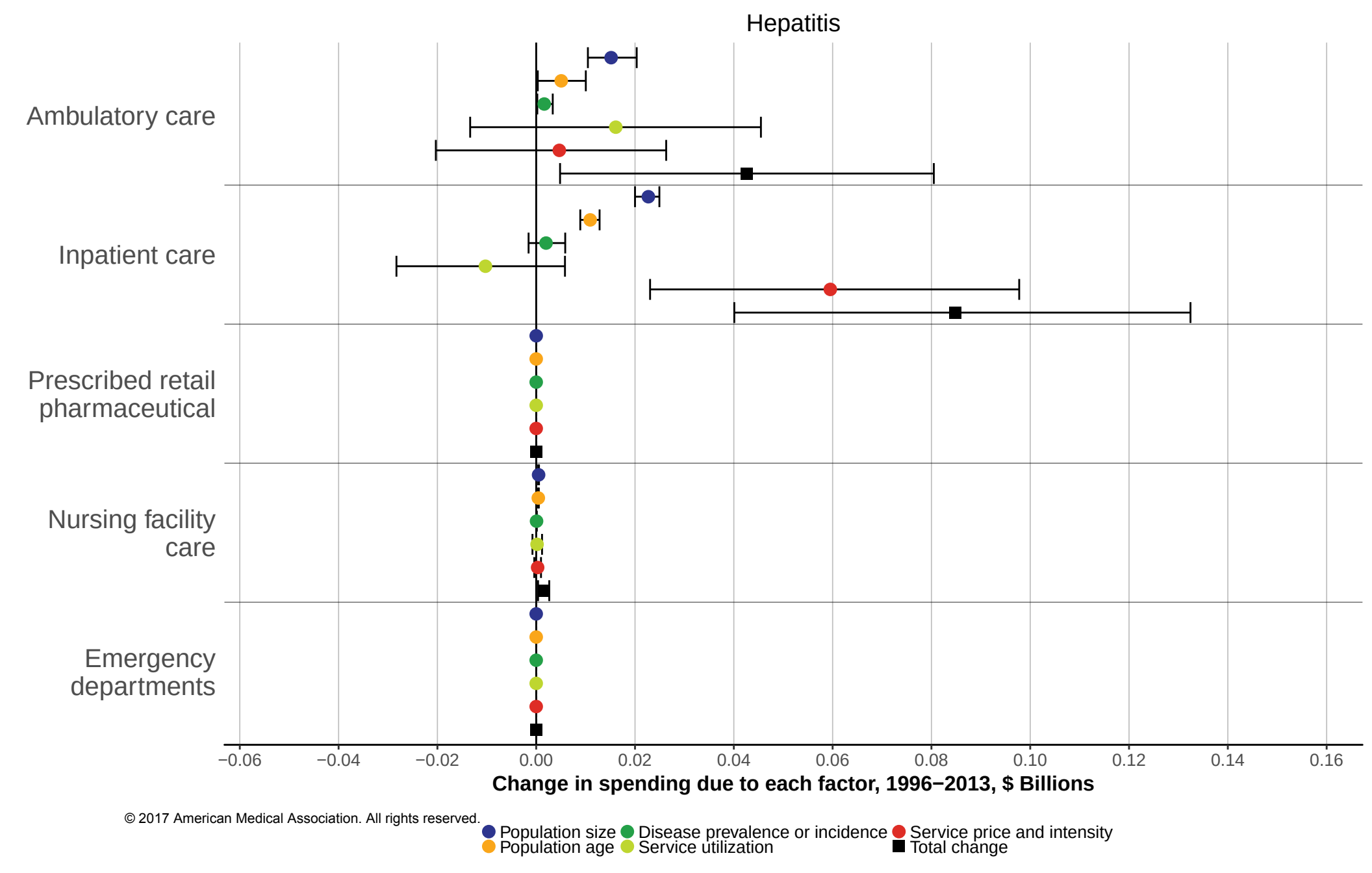


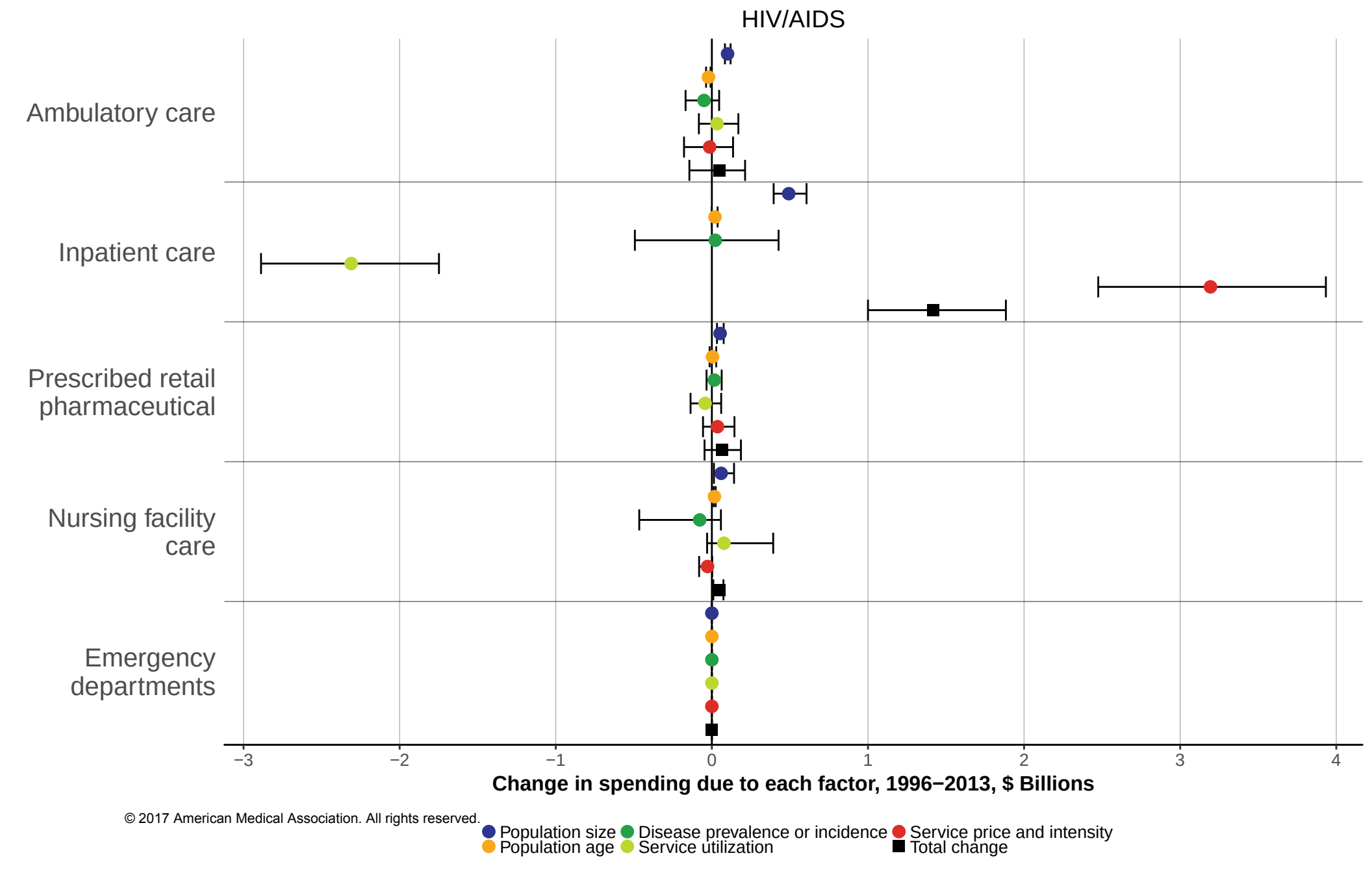
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

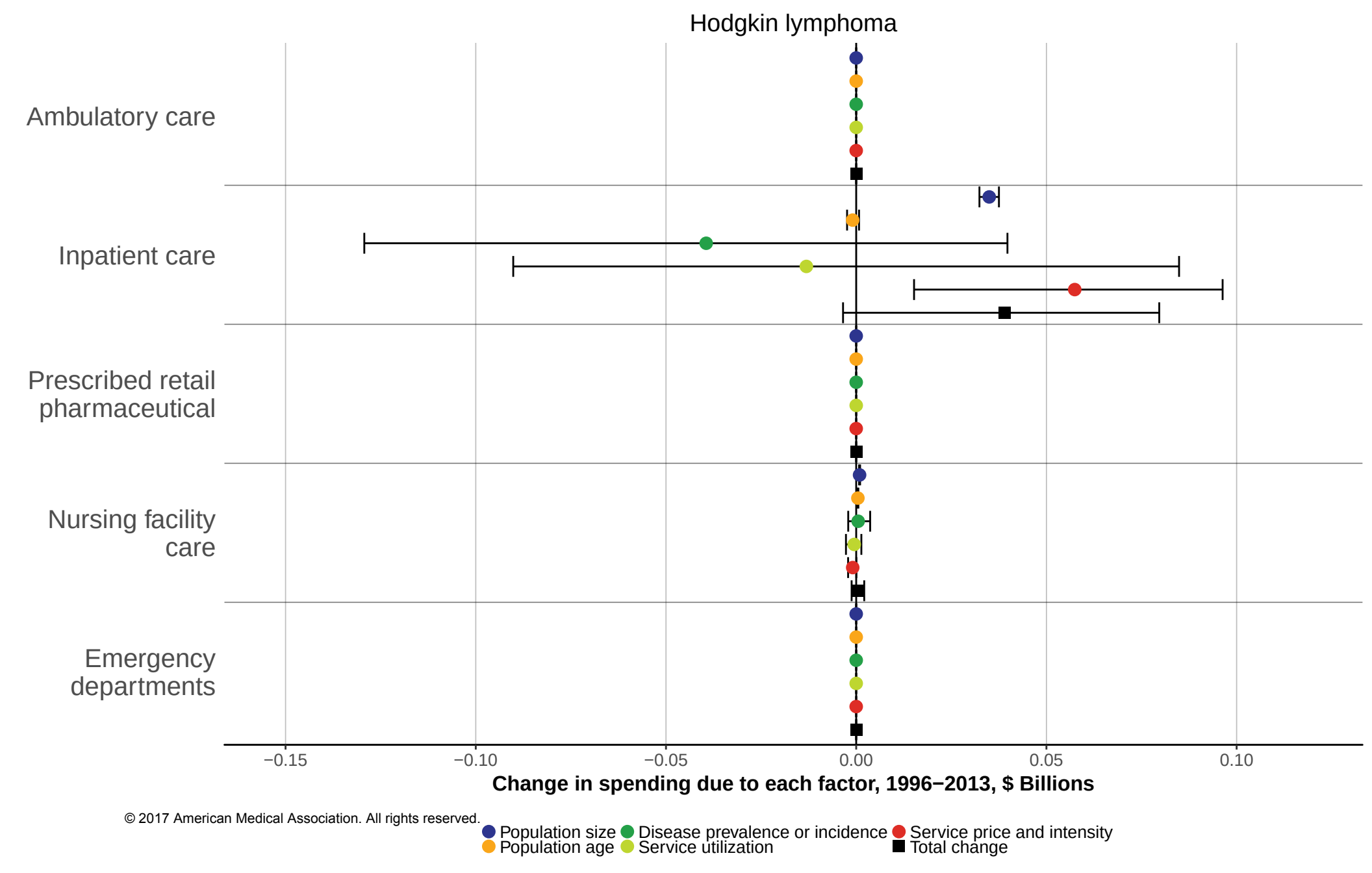


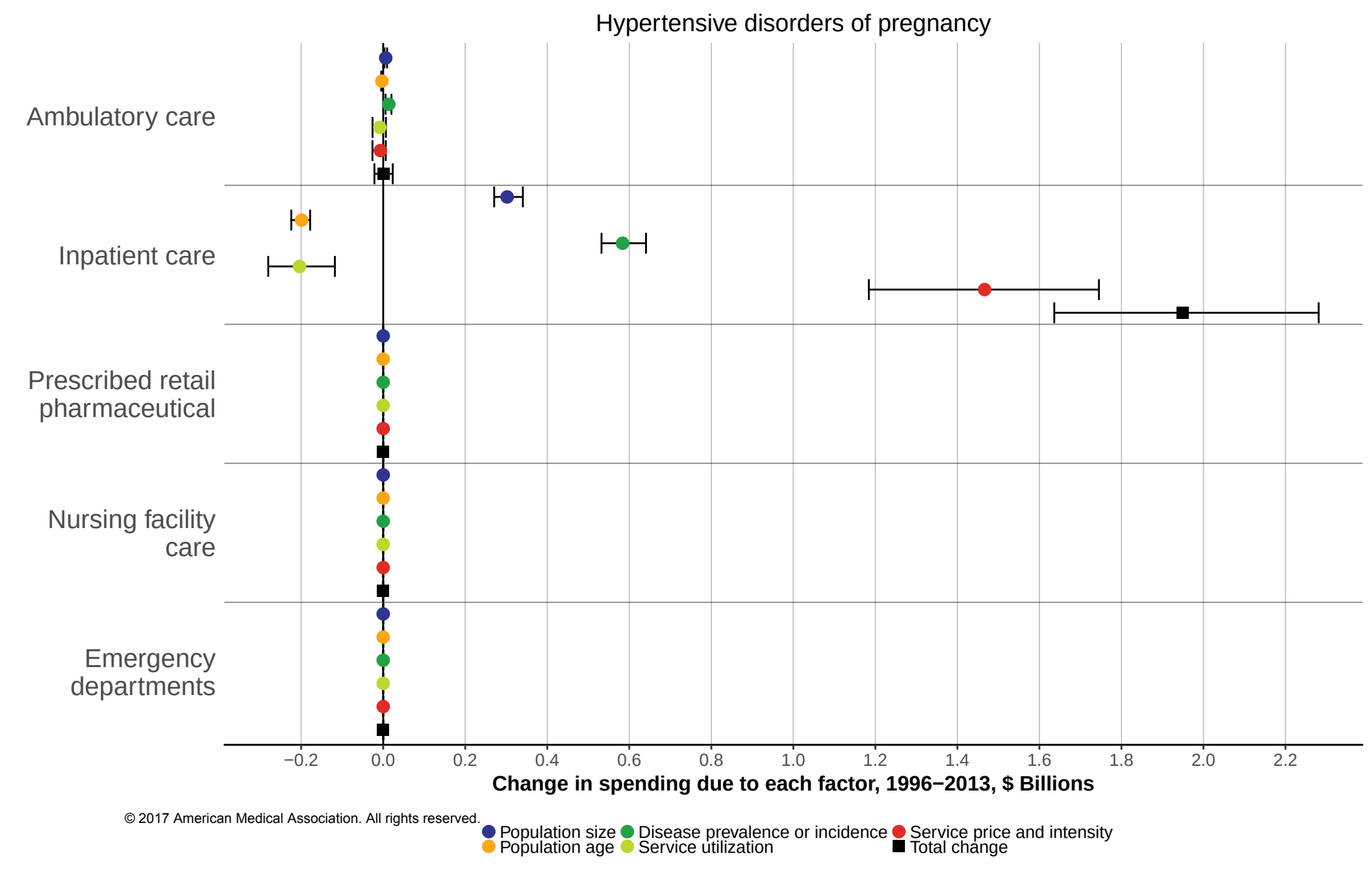


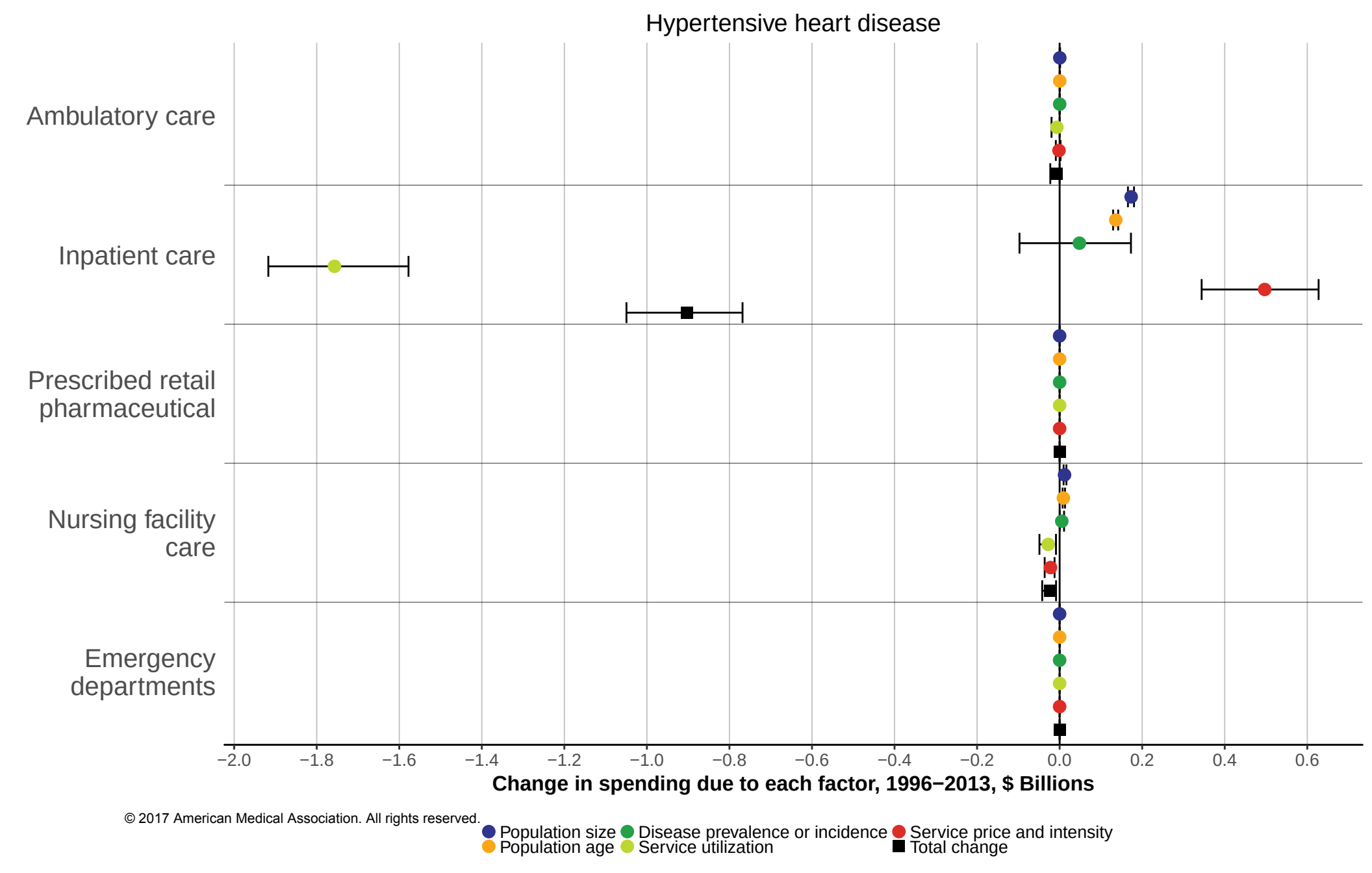


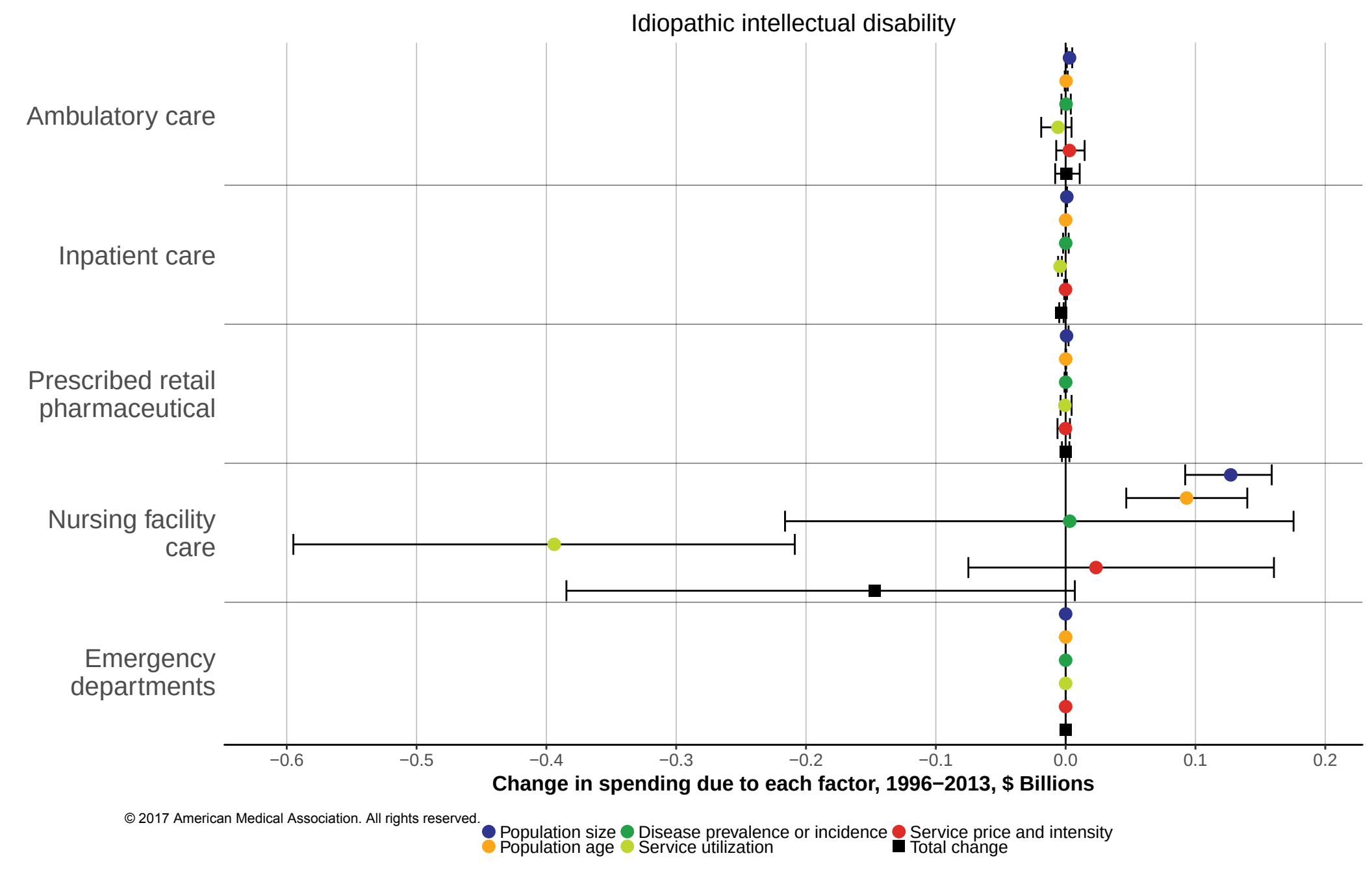


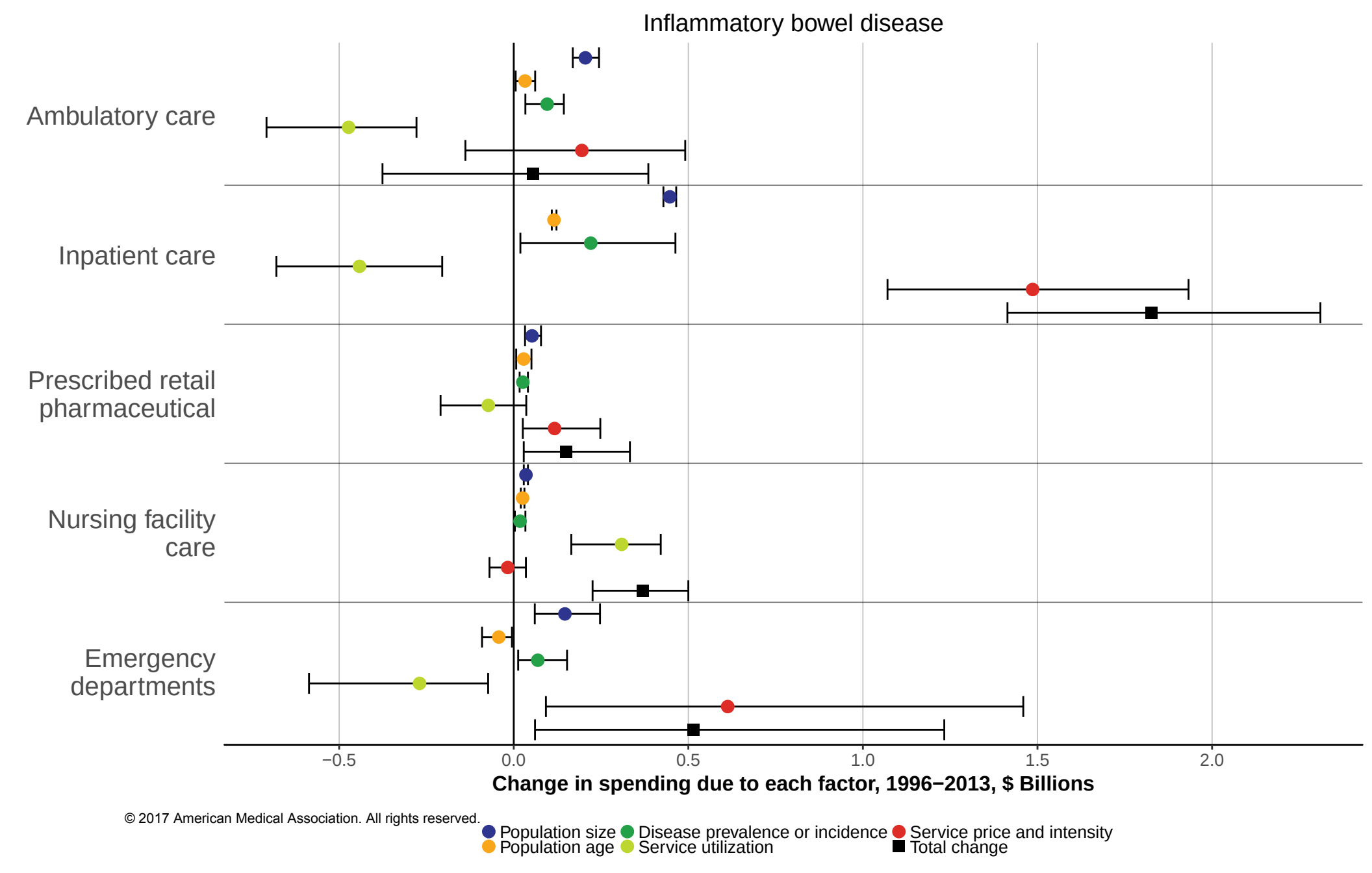


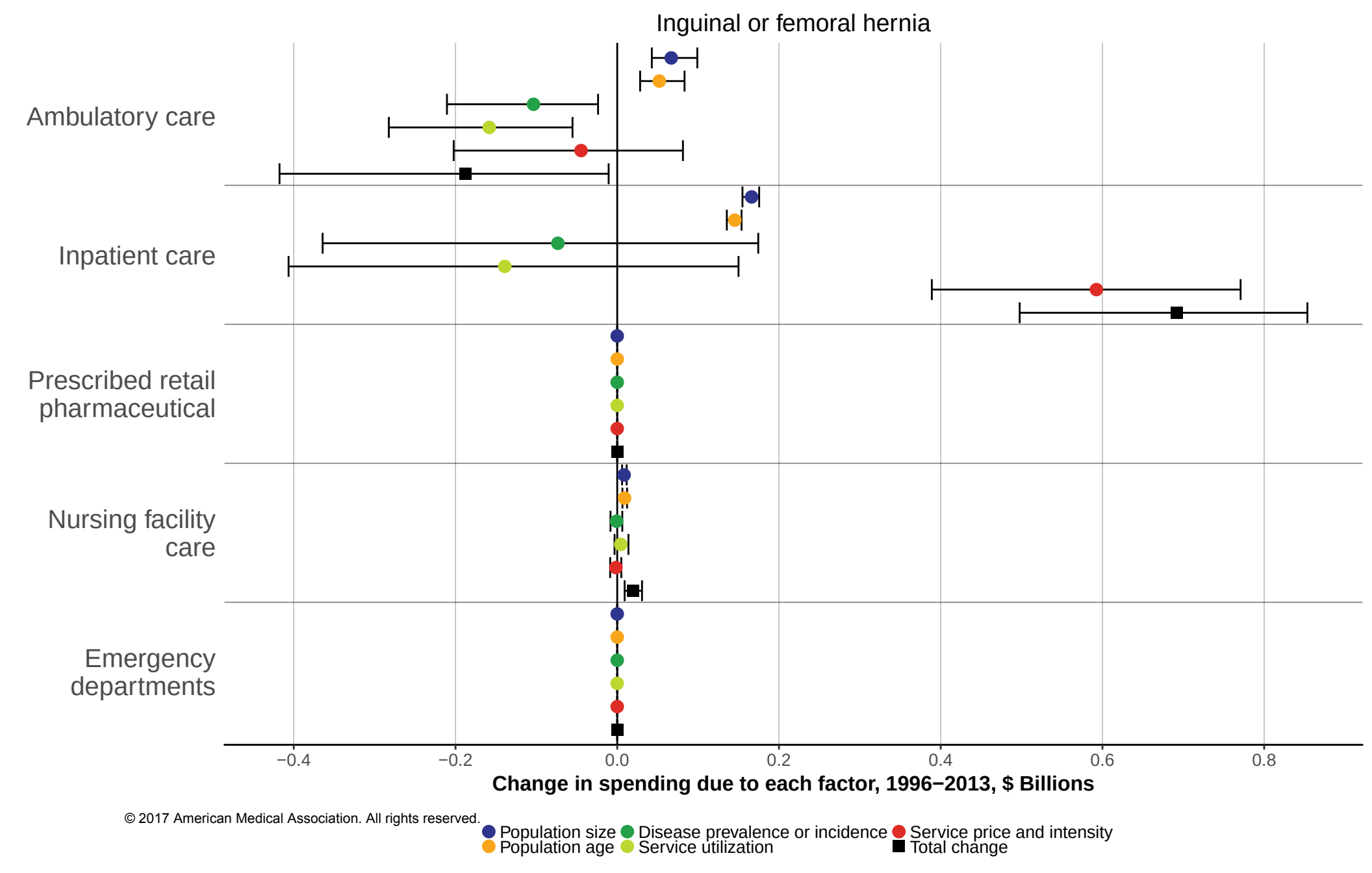


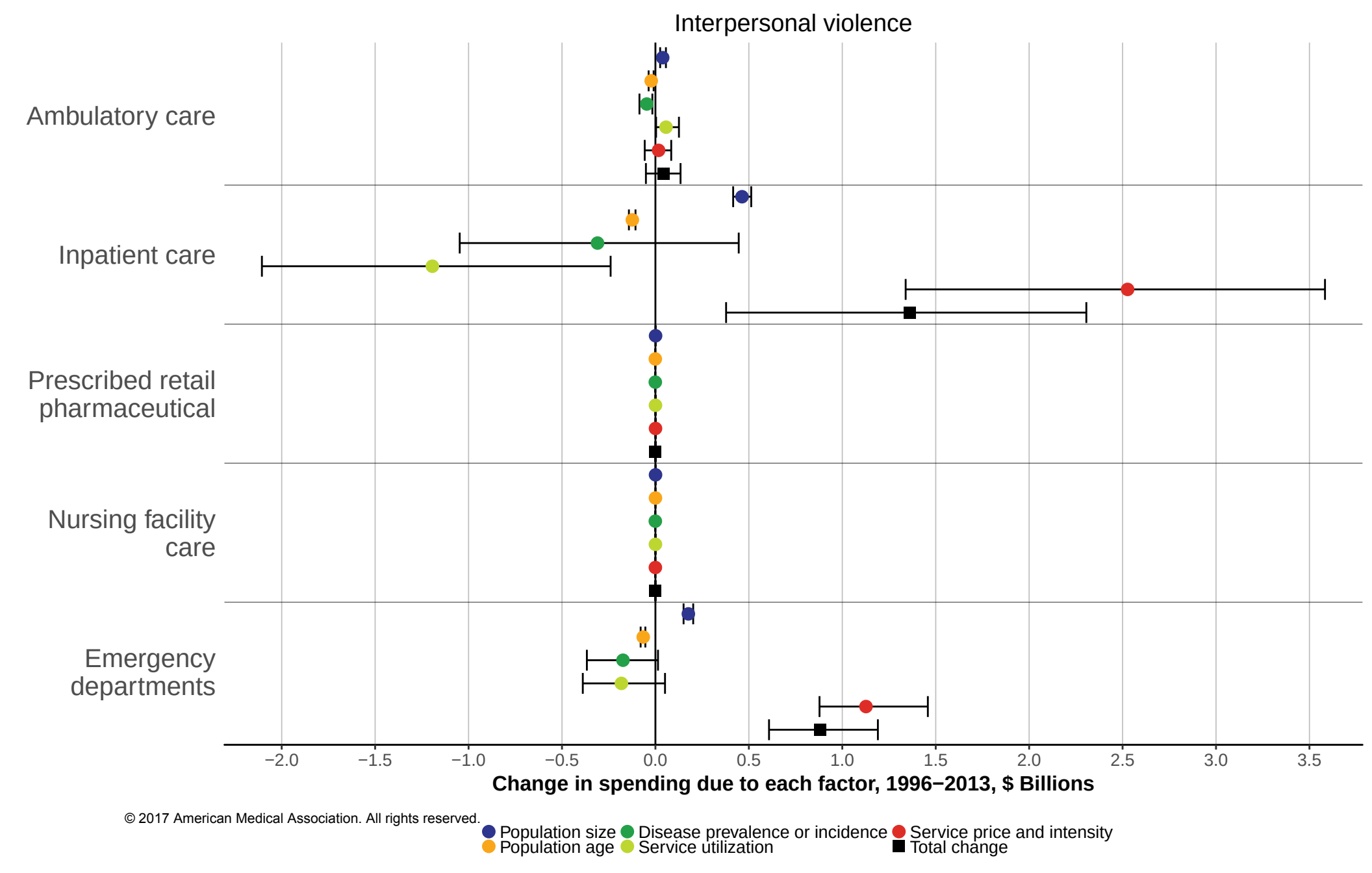


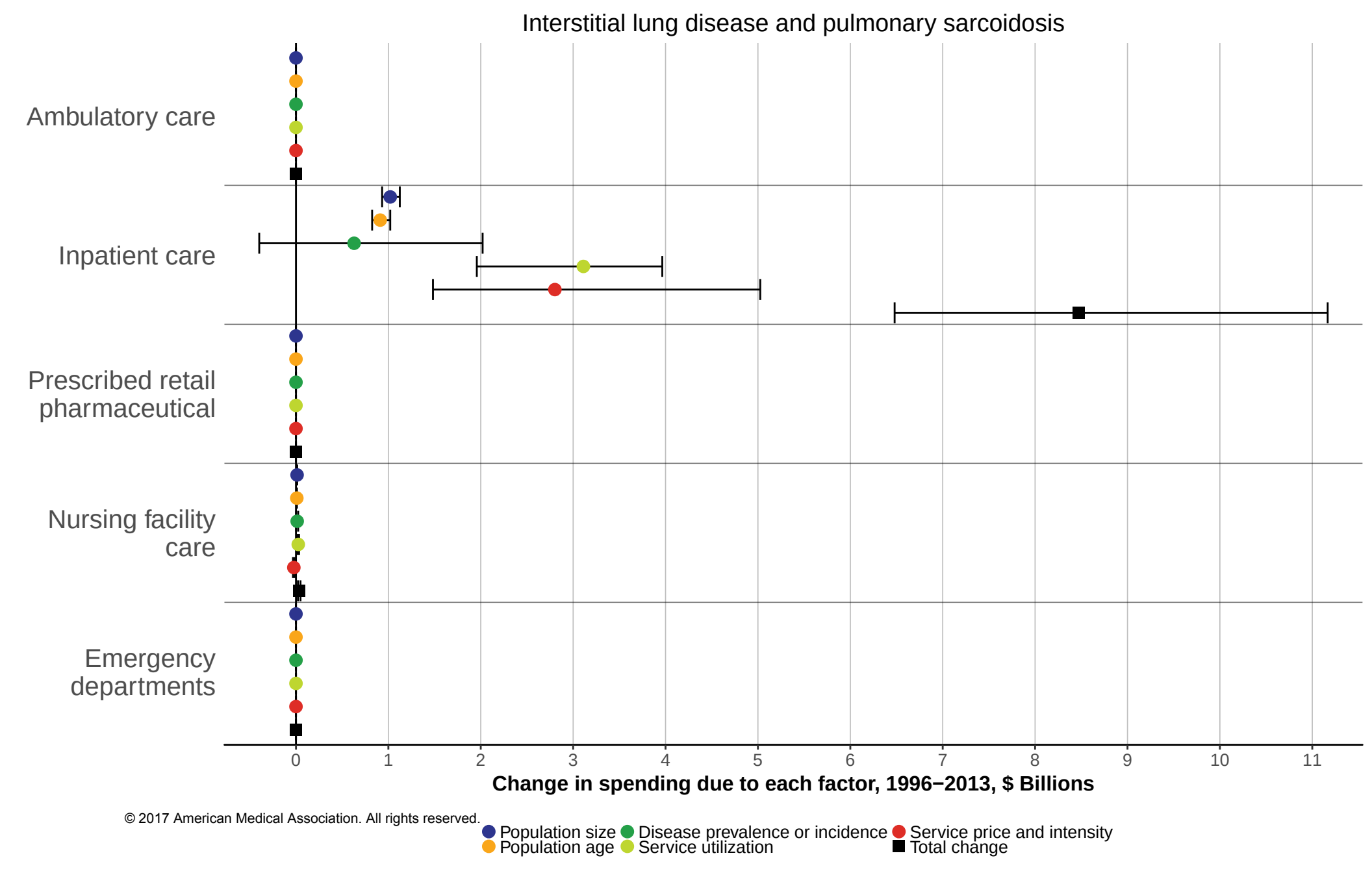


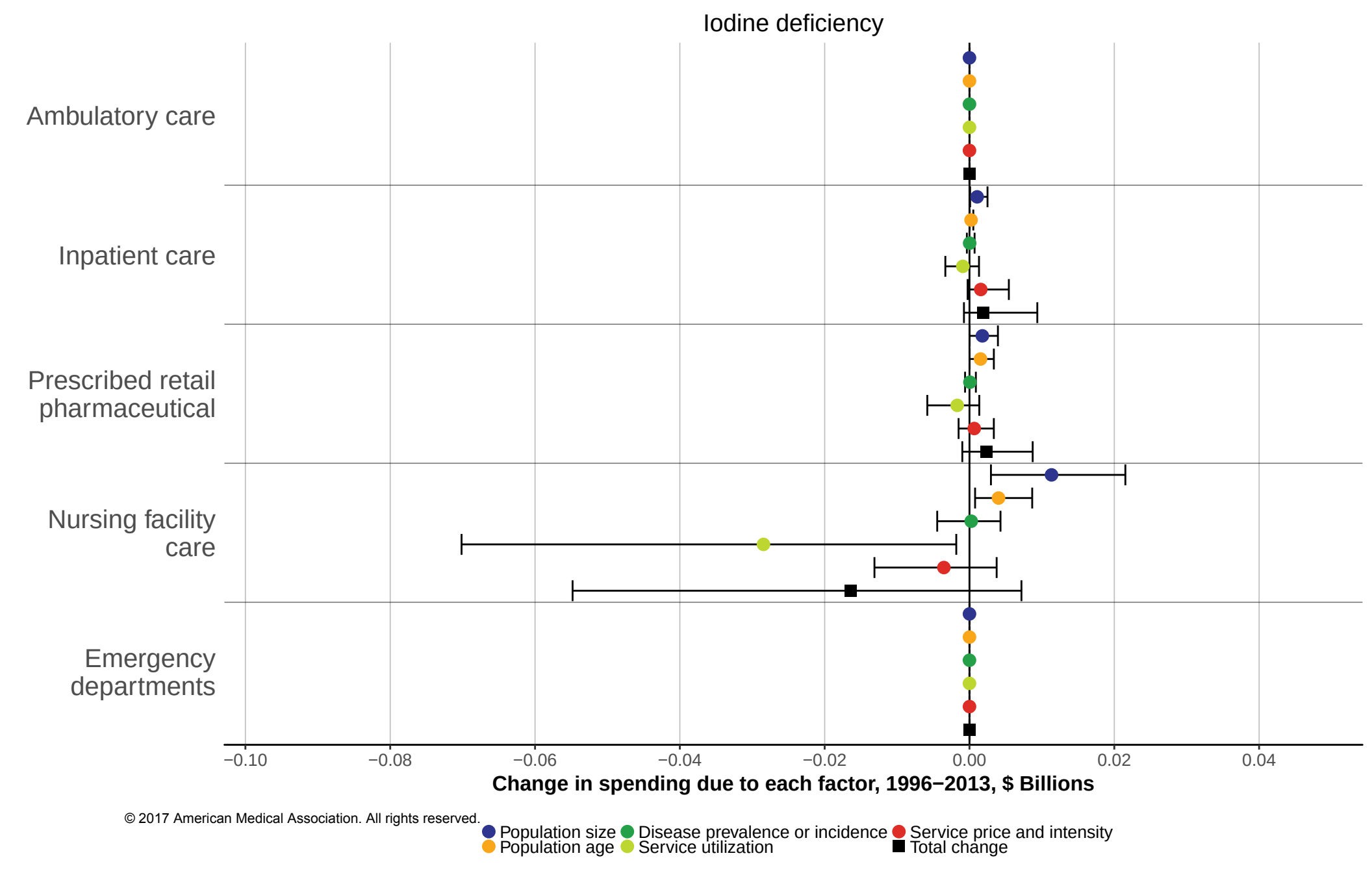


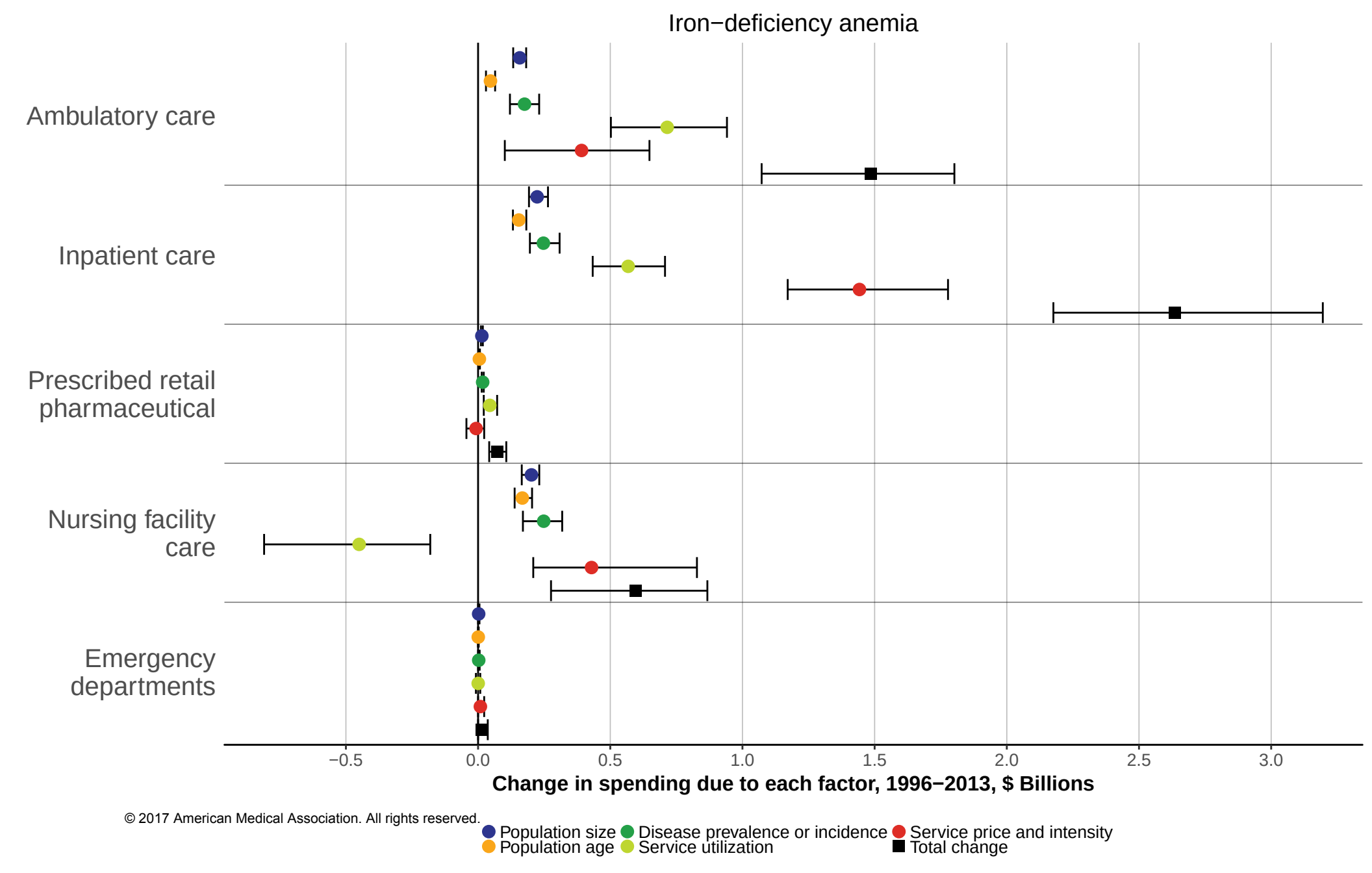




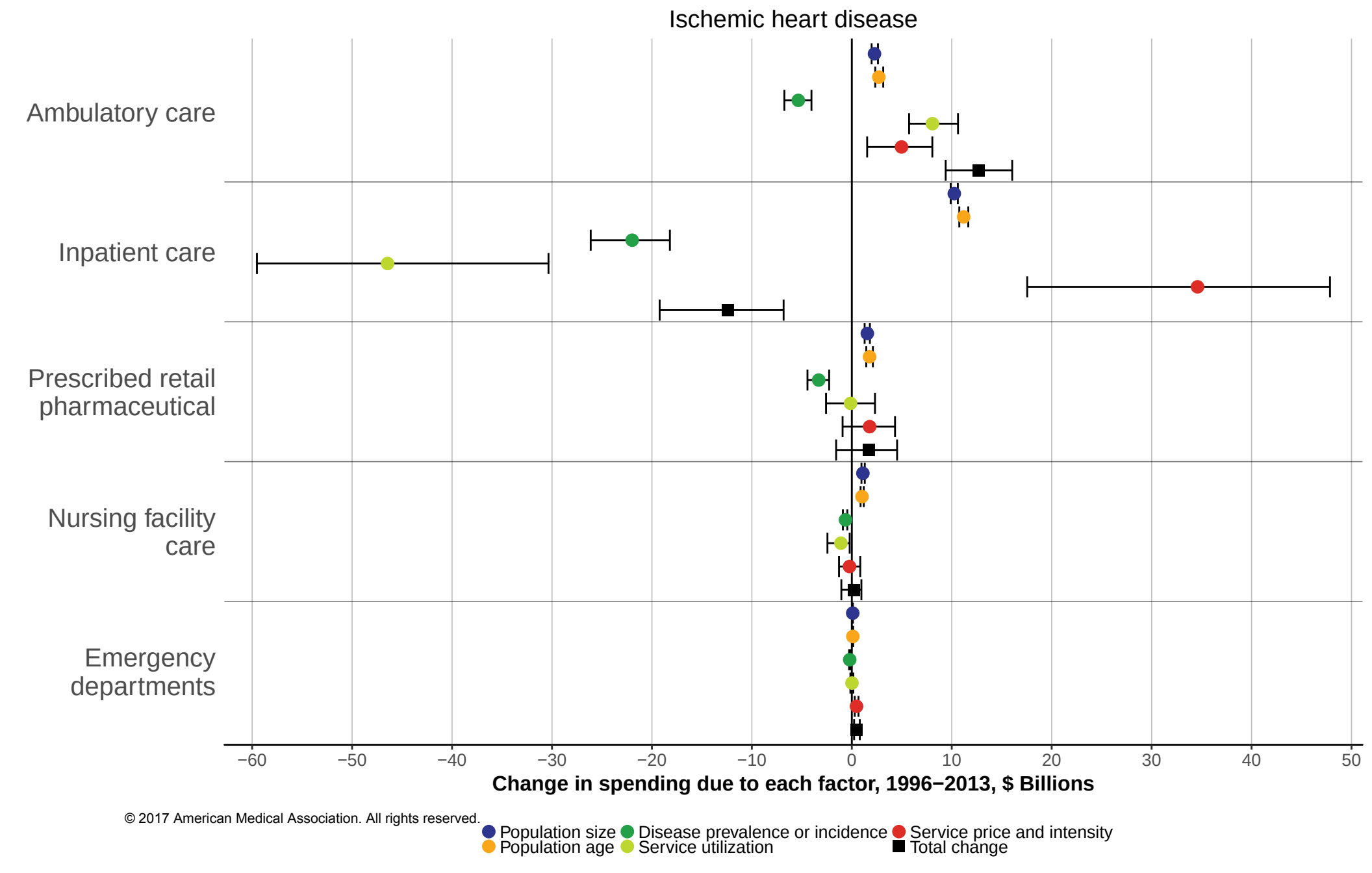




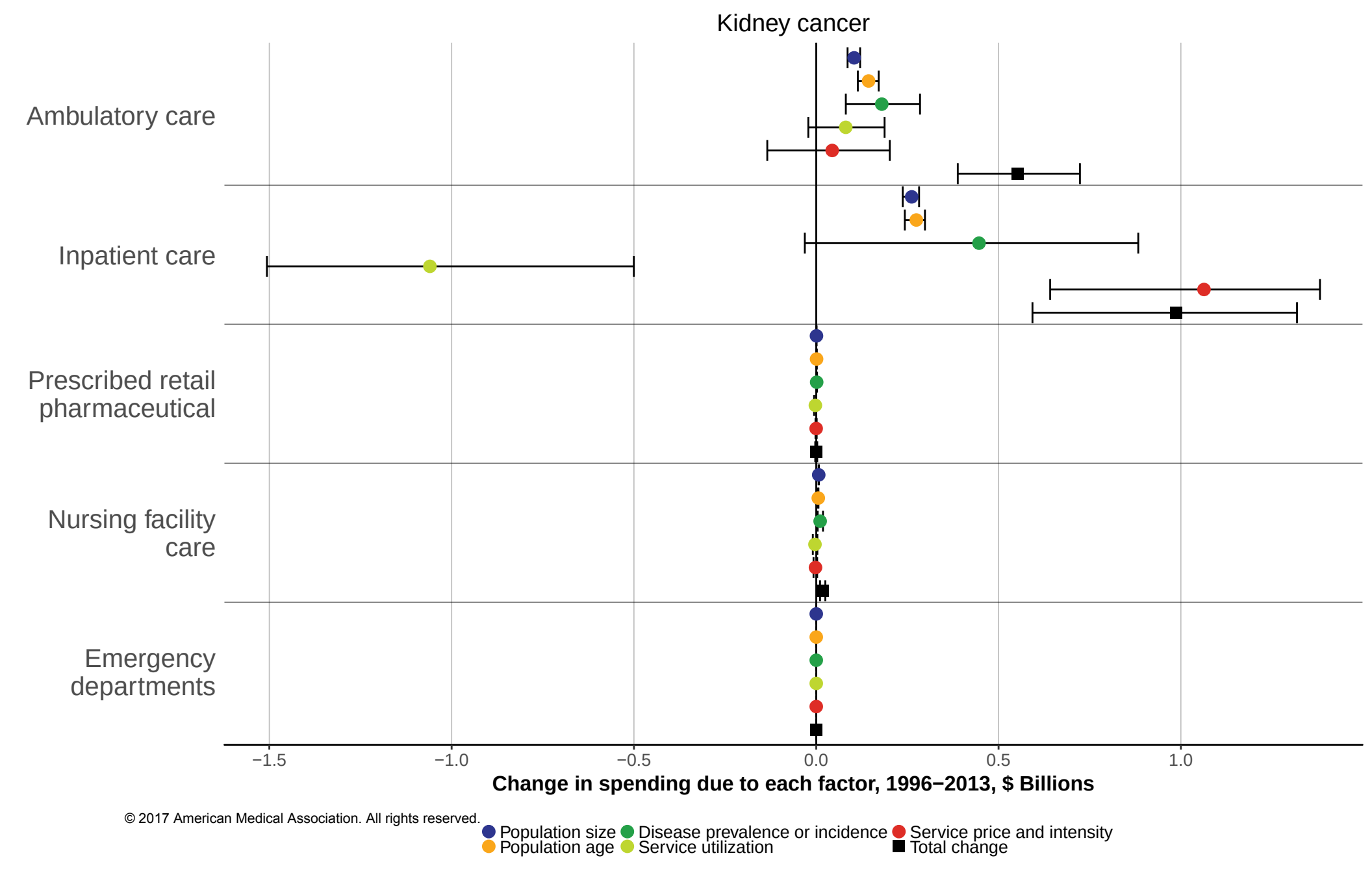


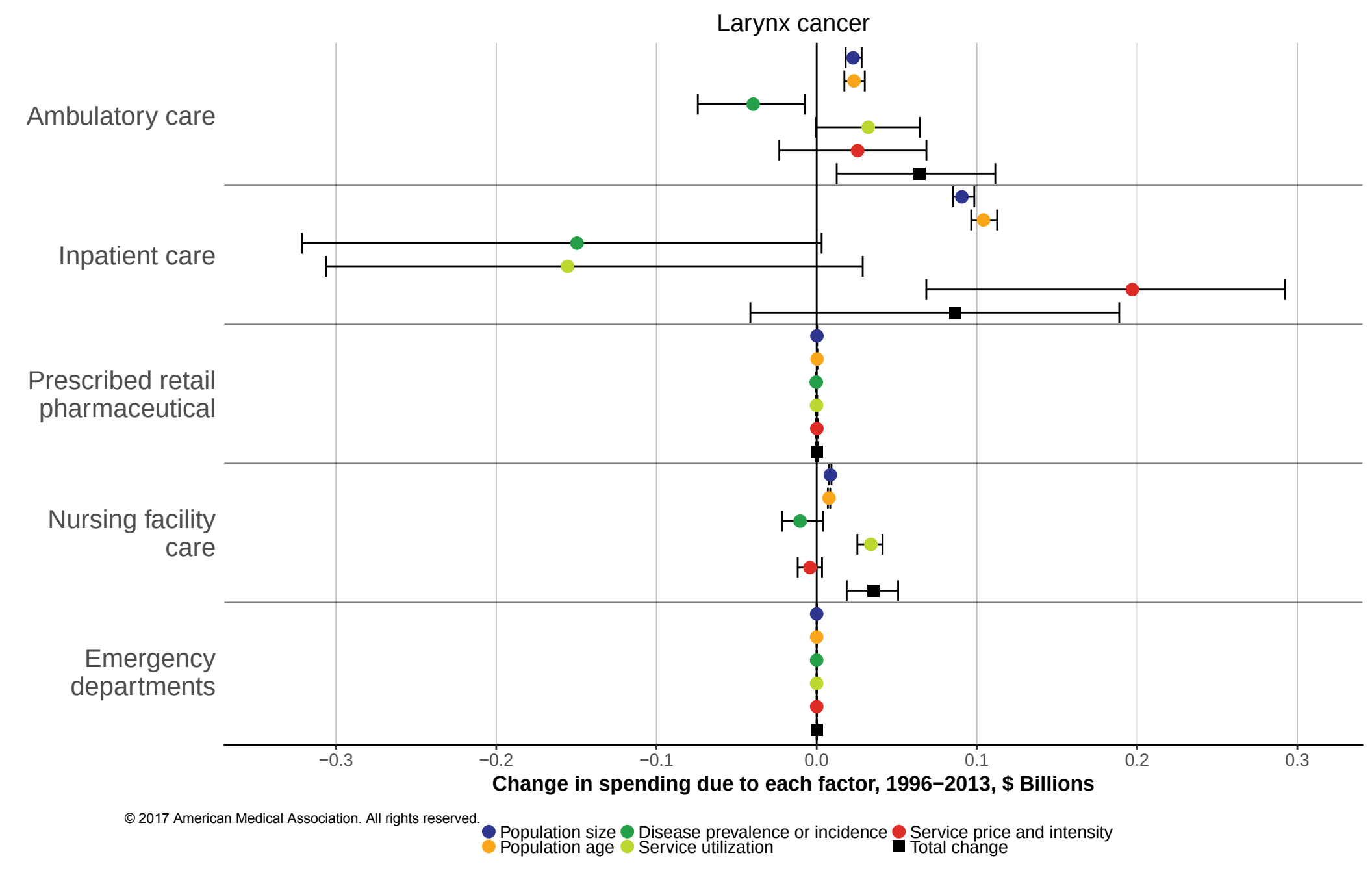


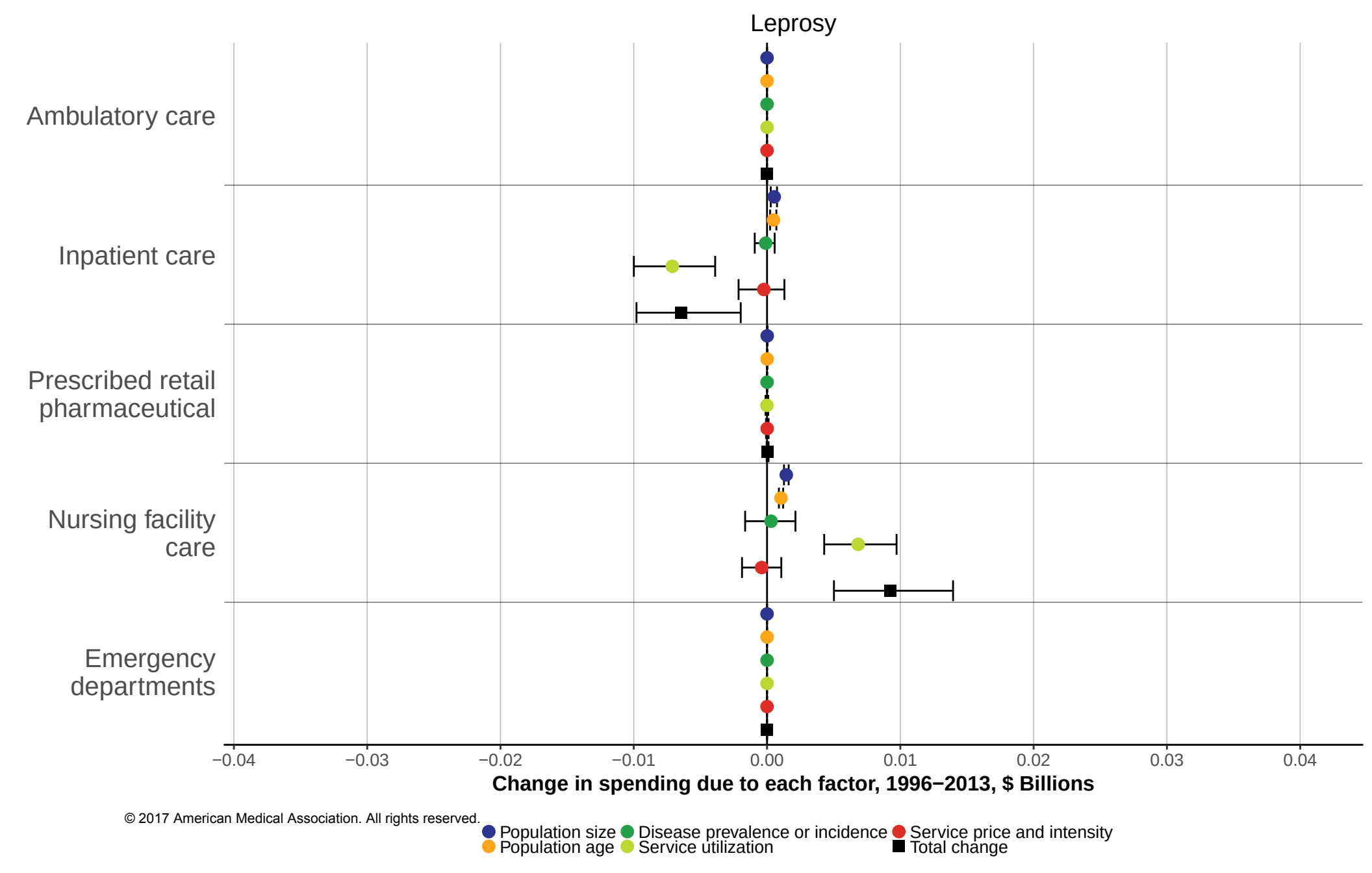
Population size
Population age
Disease prevalence or incidence
Service utilization
Service price and intensity
Total change

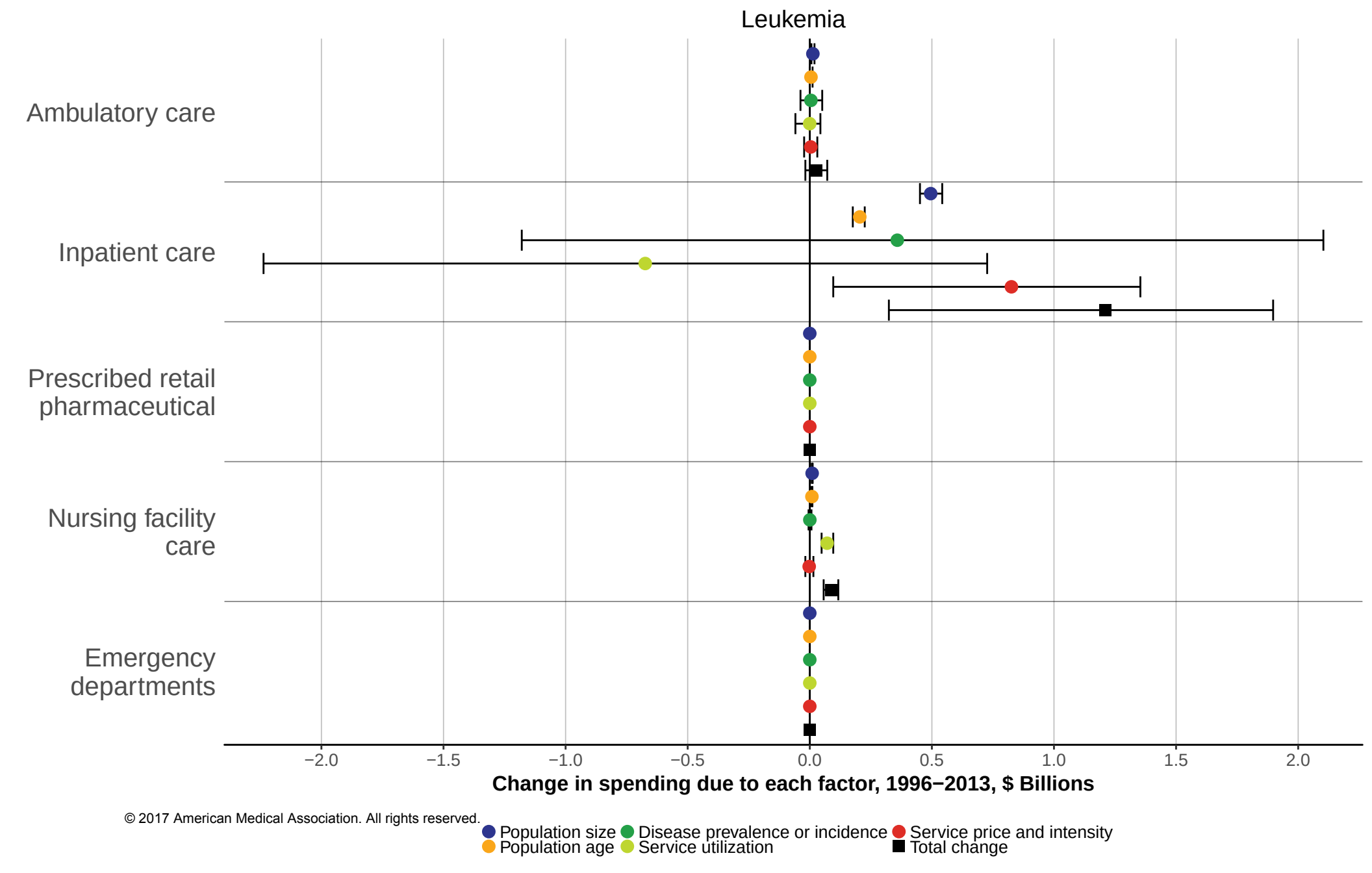


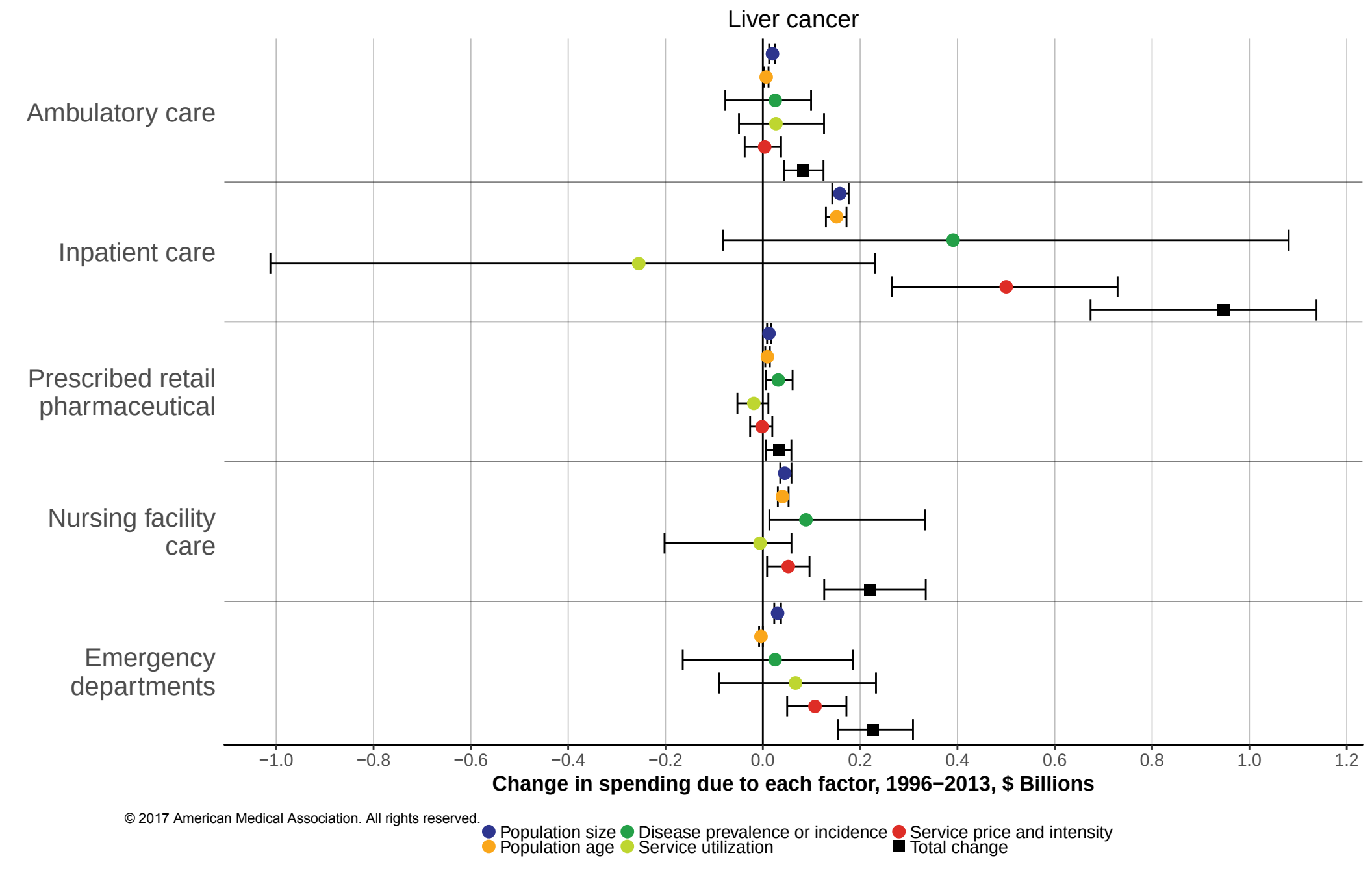
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

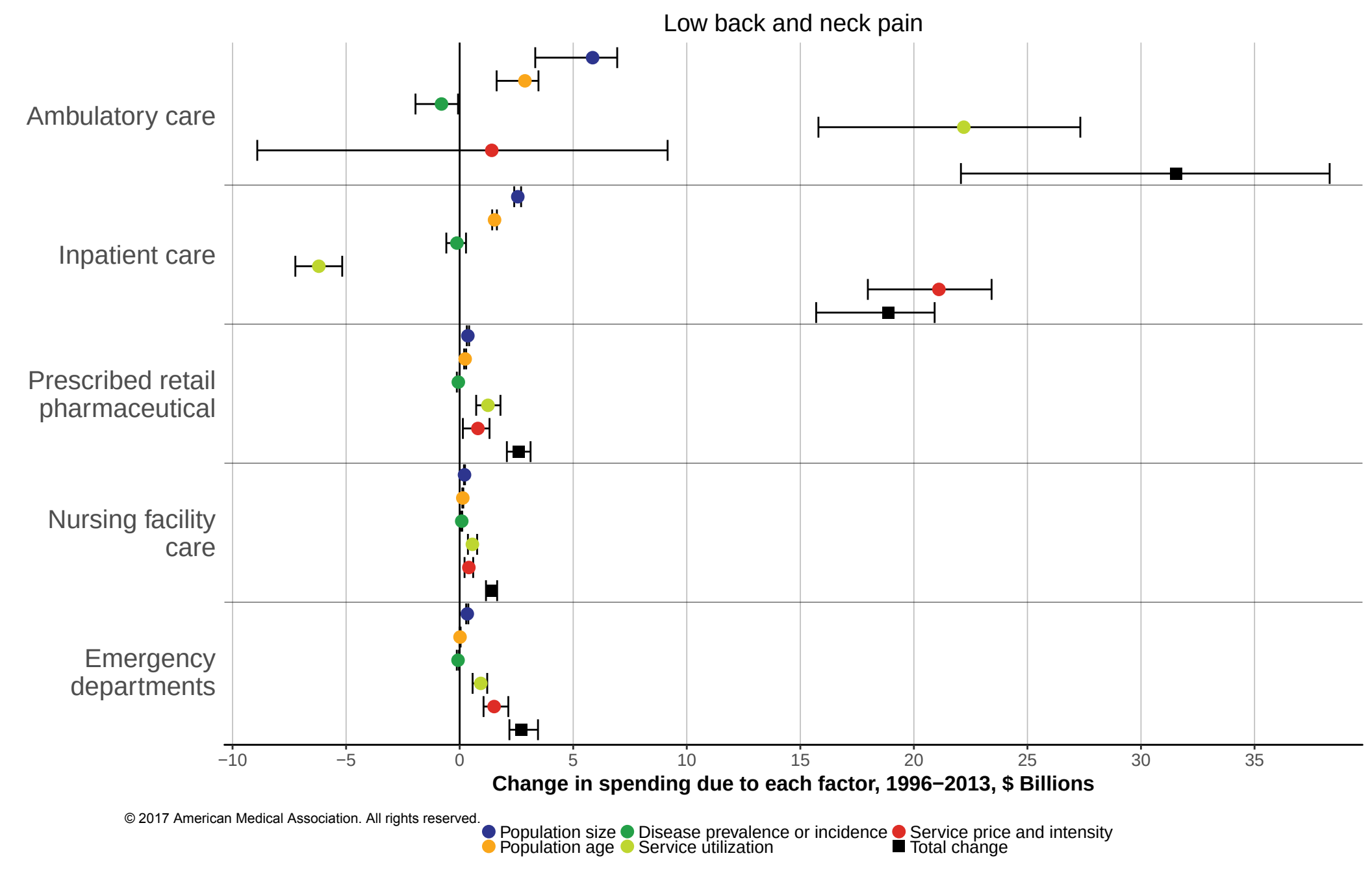


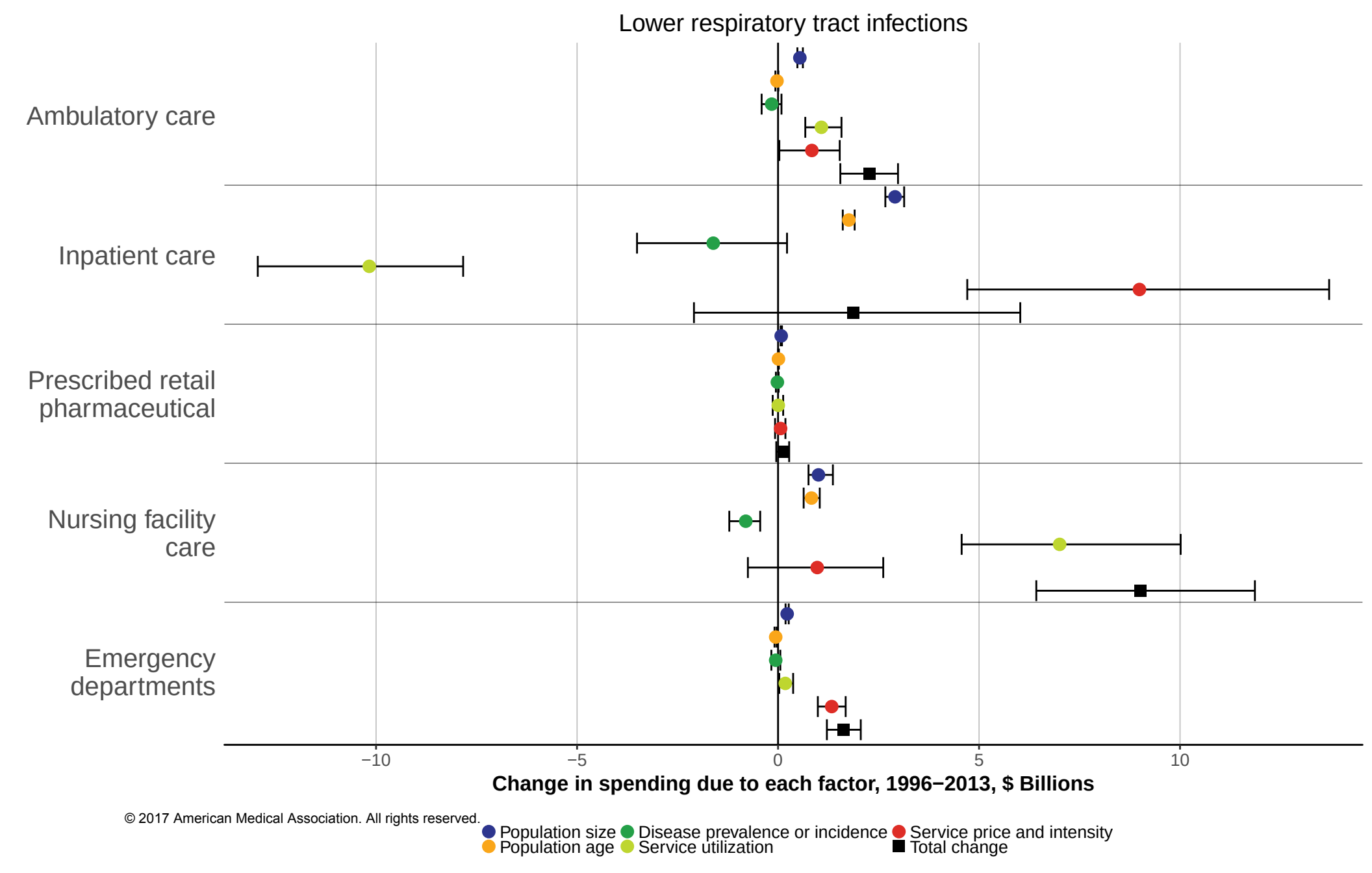


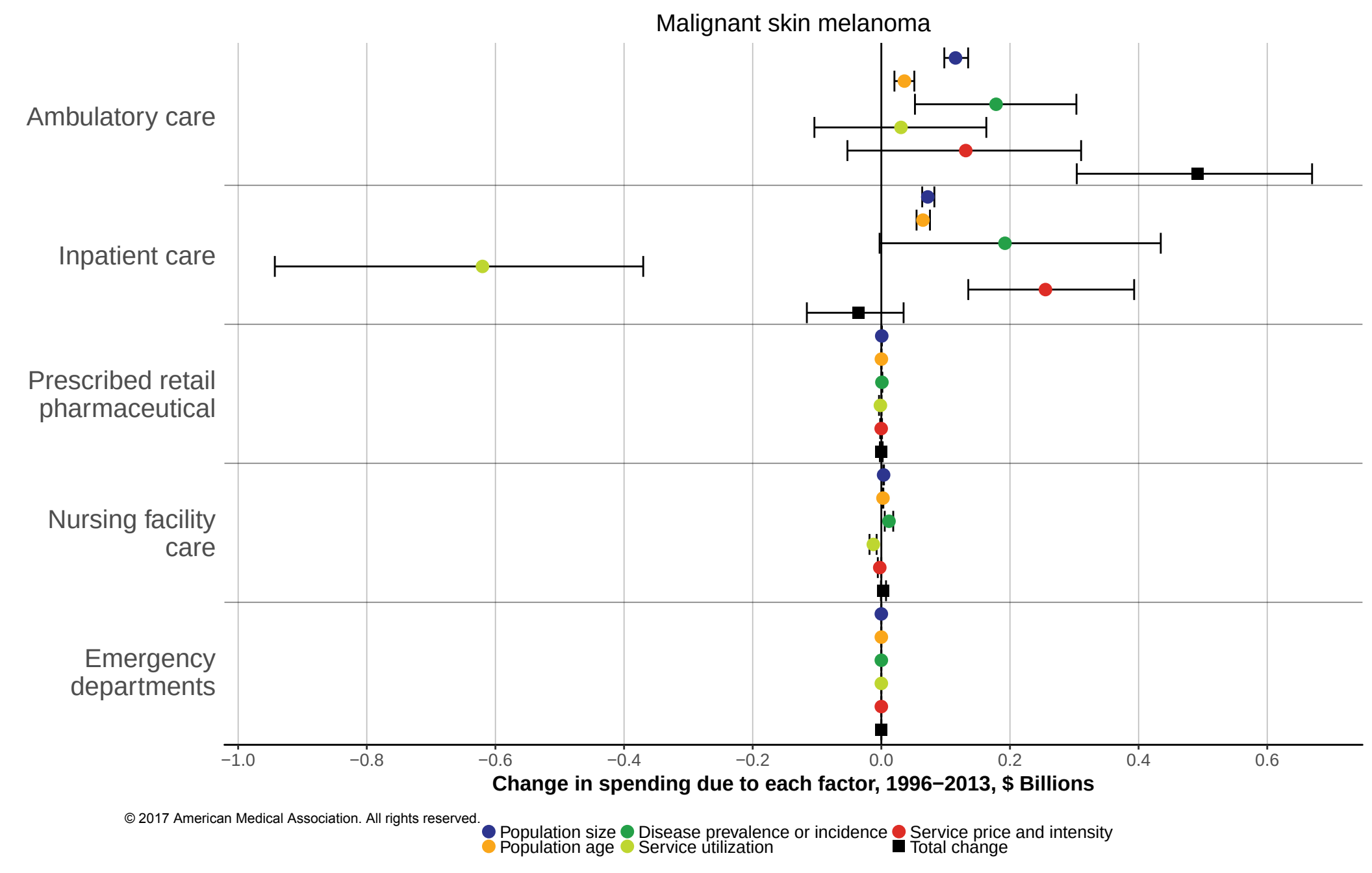


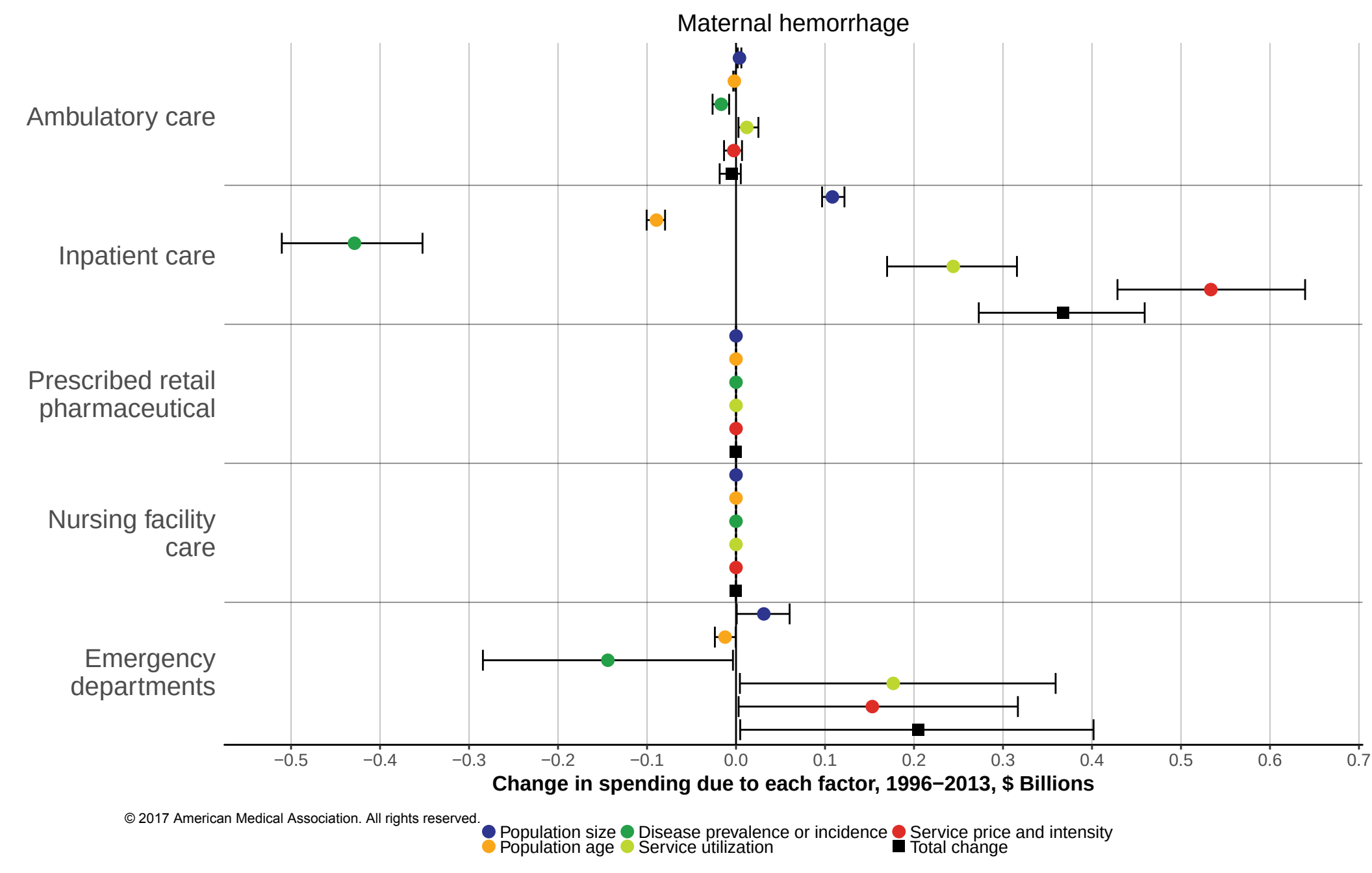


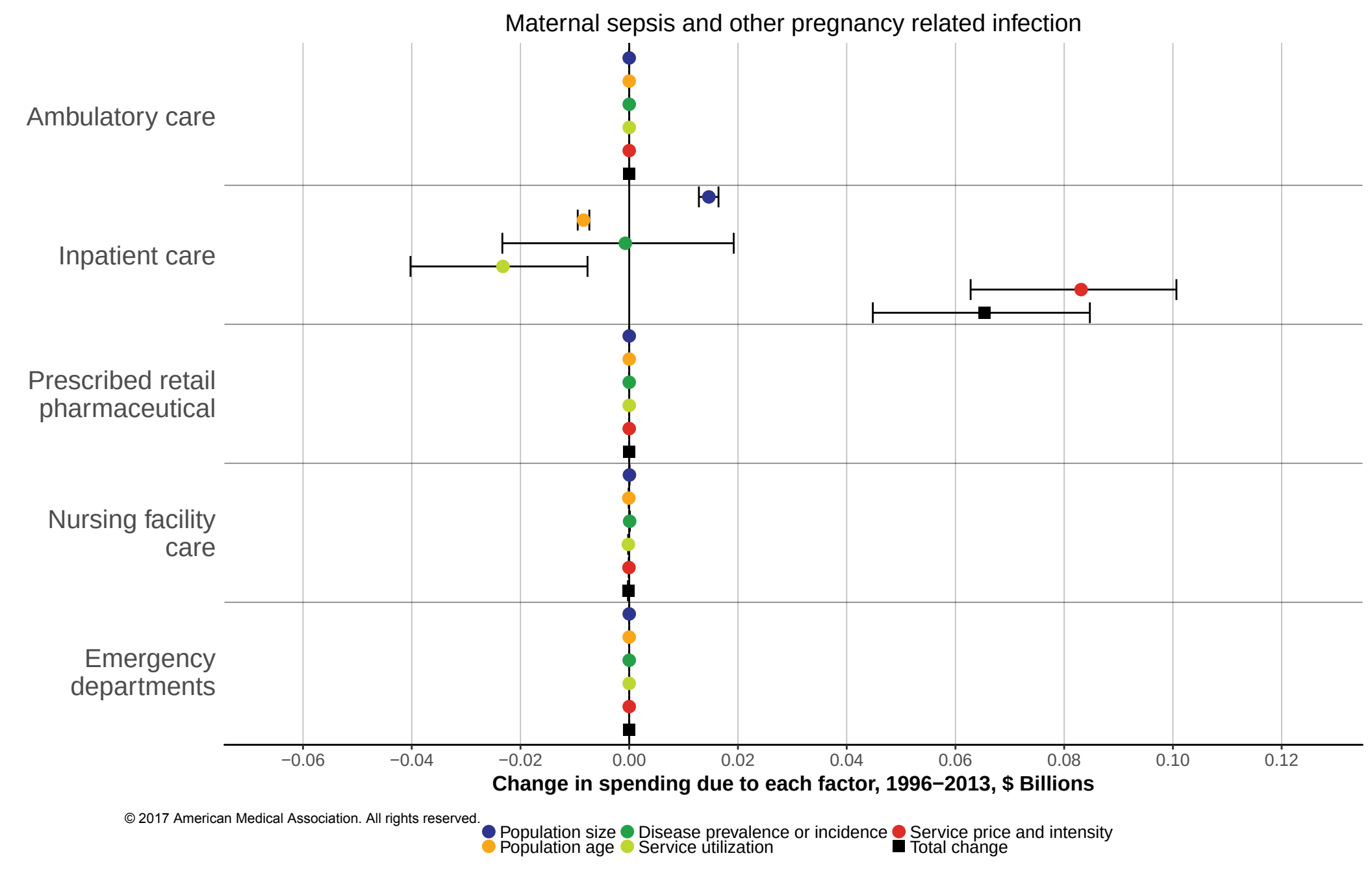


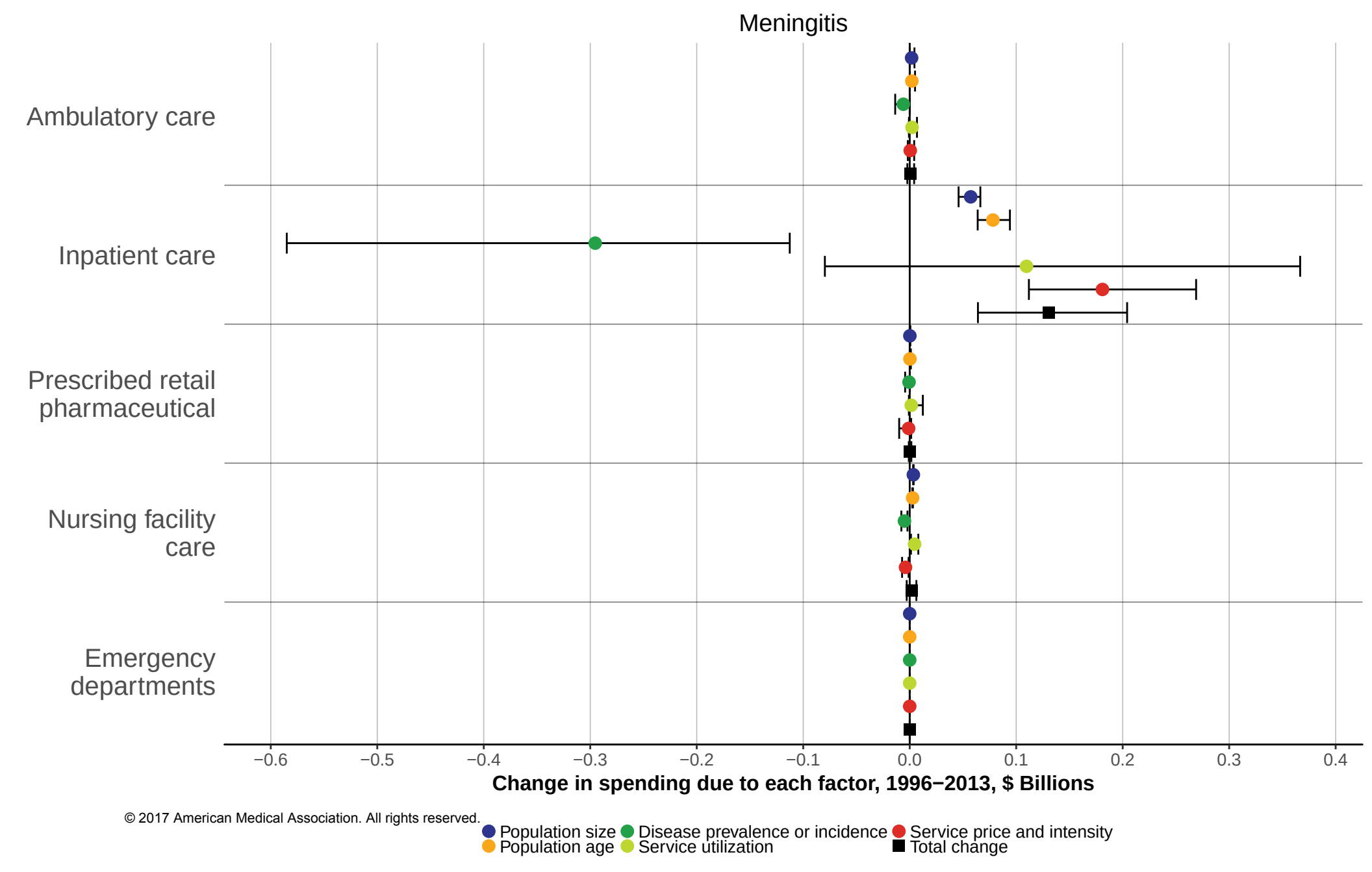


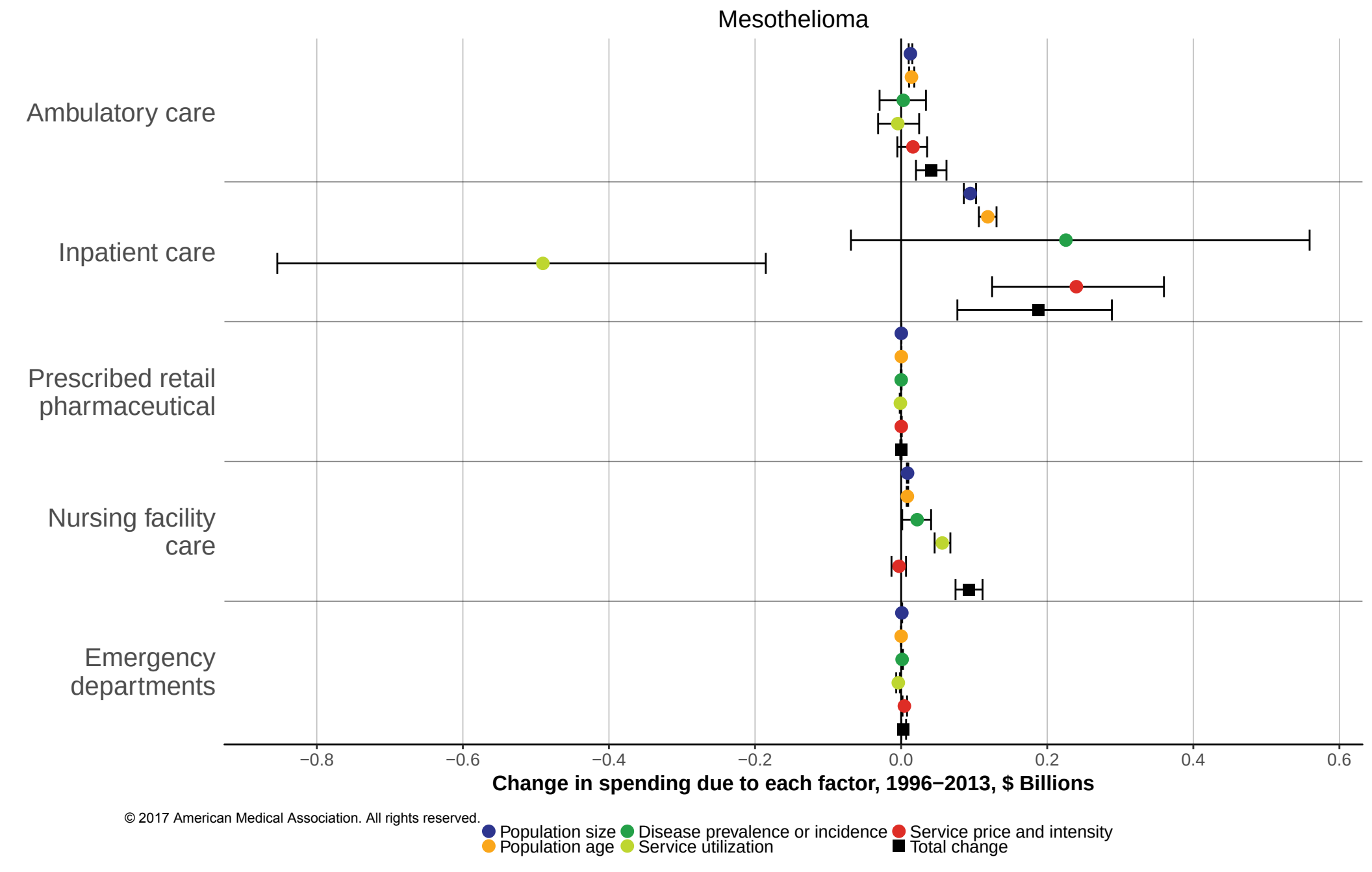


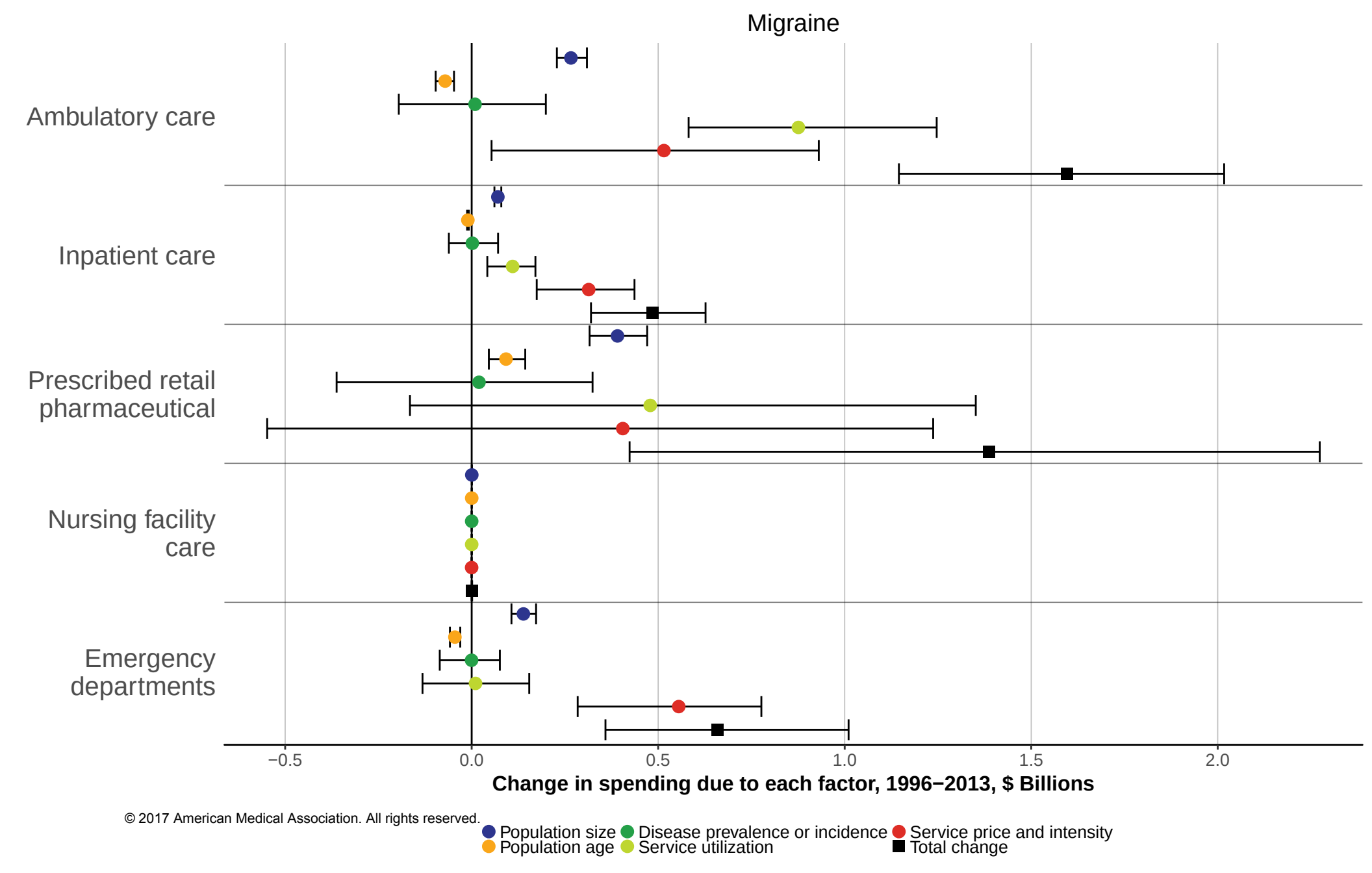


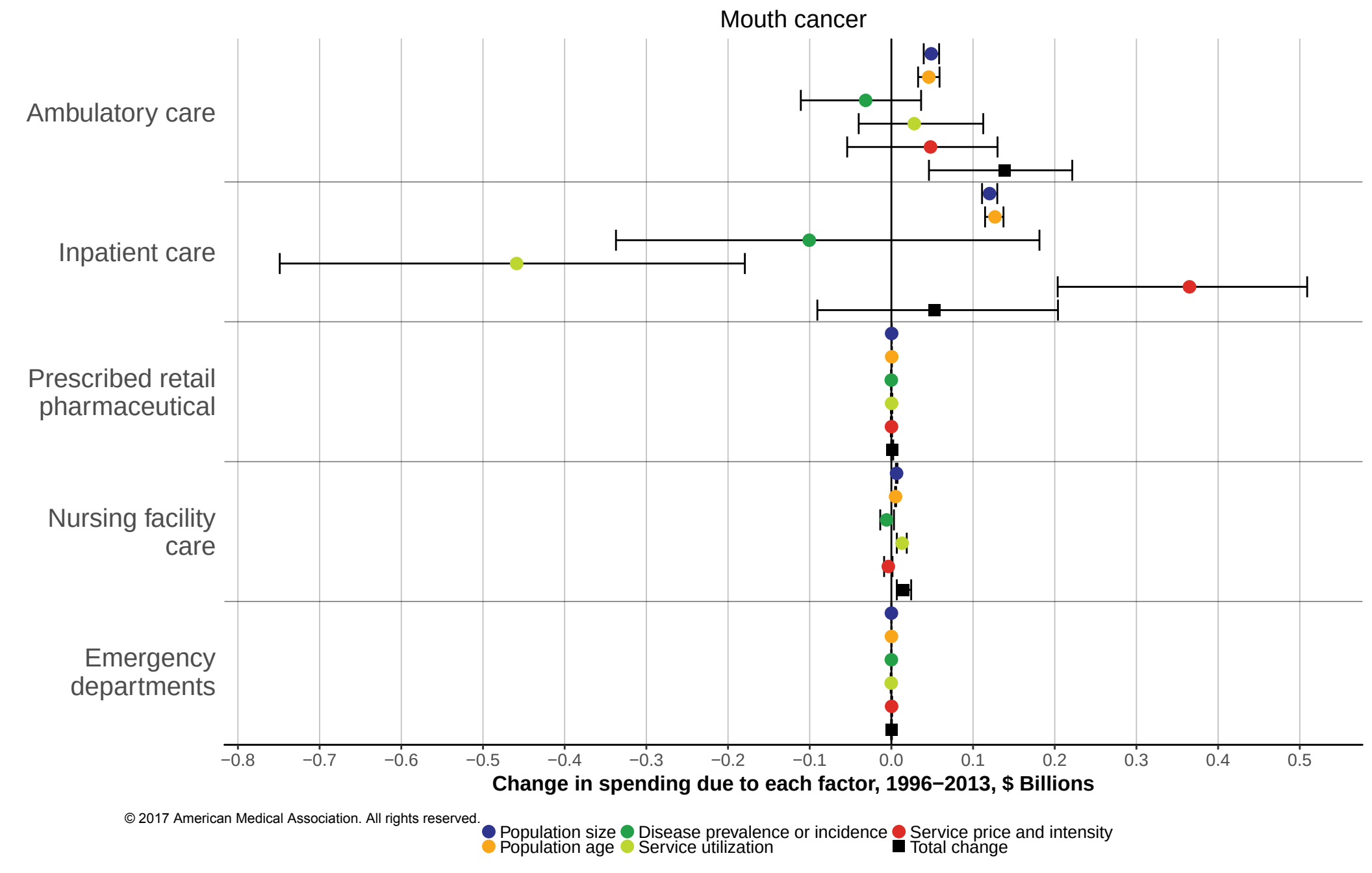


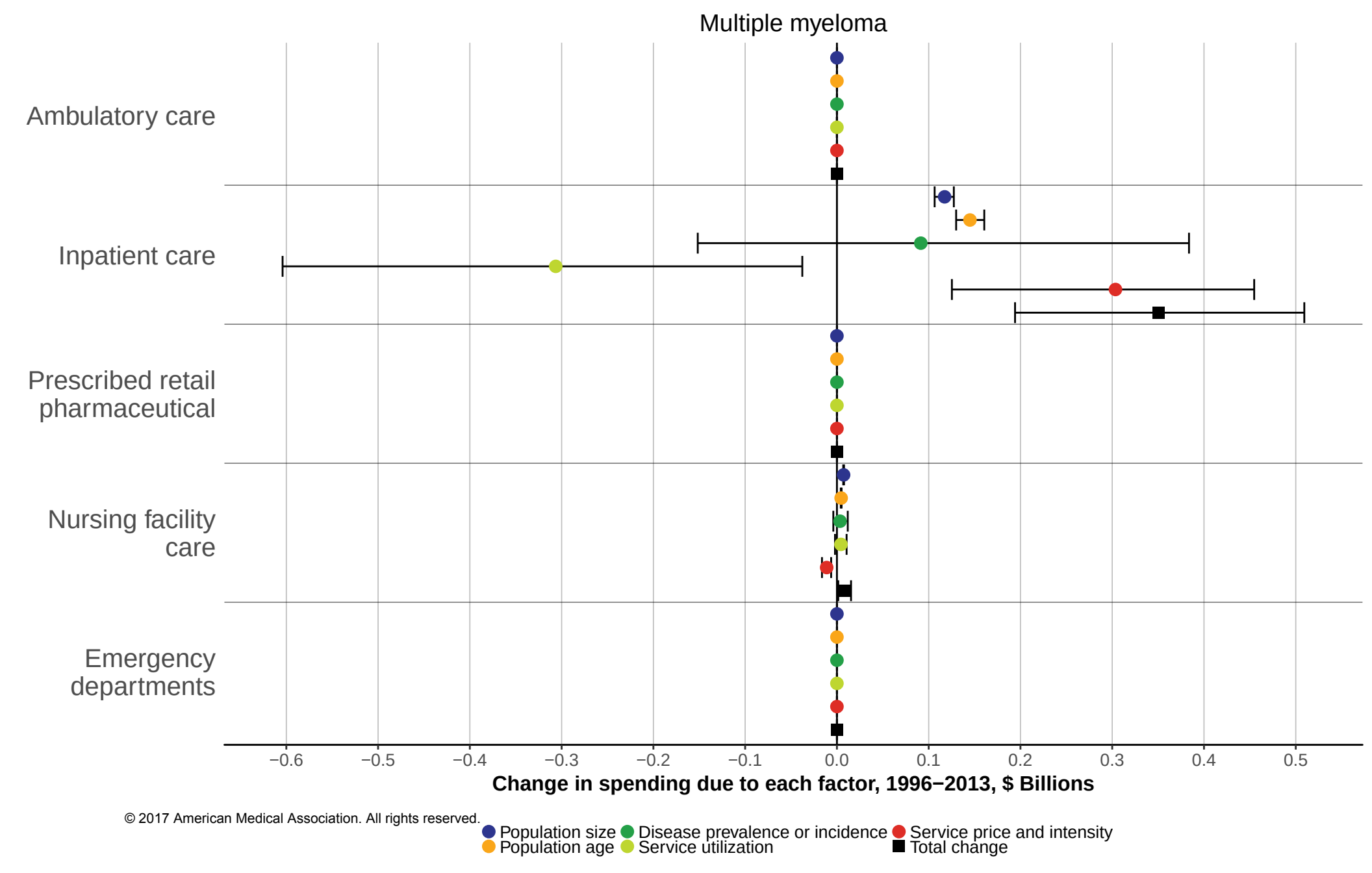


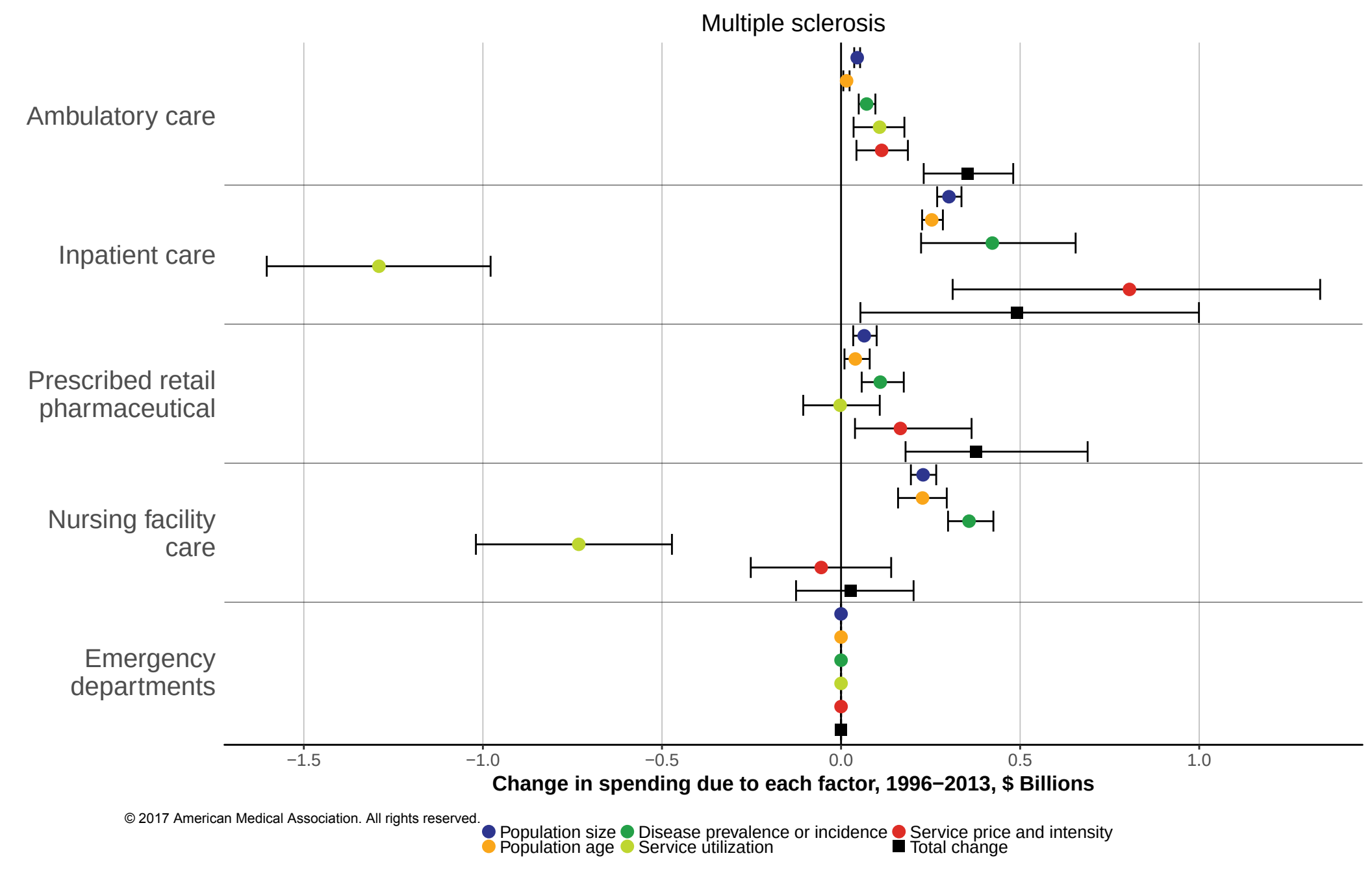




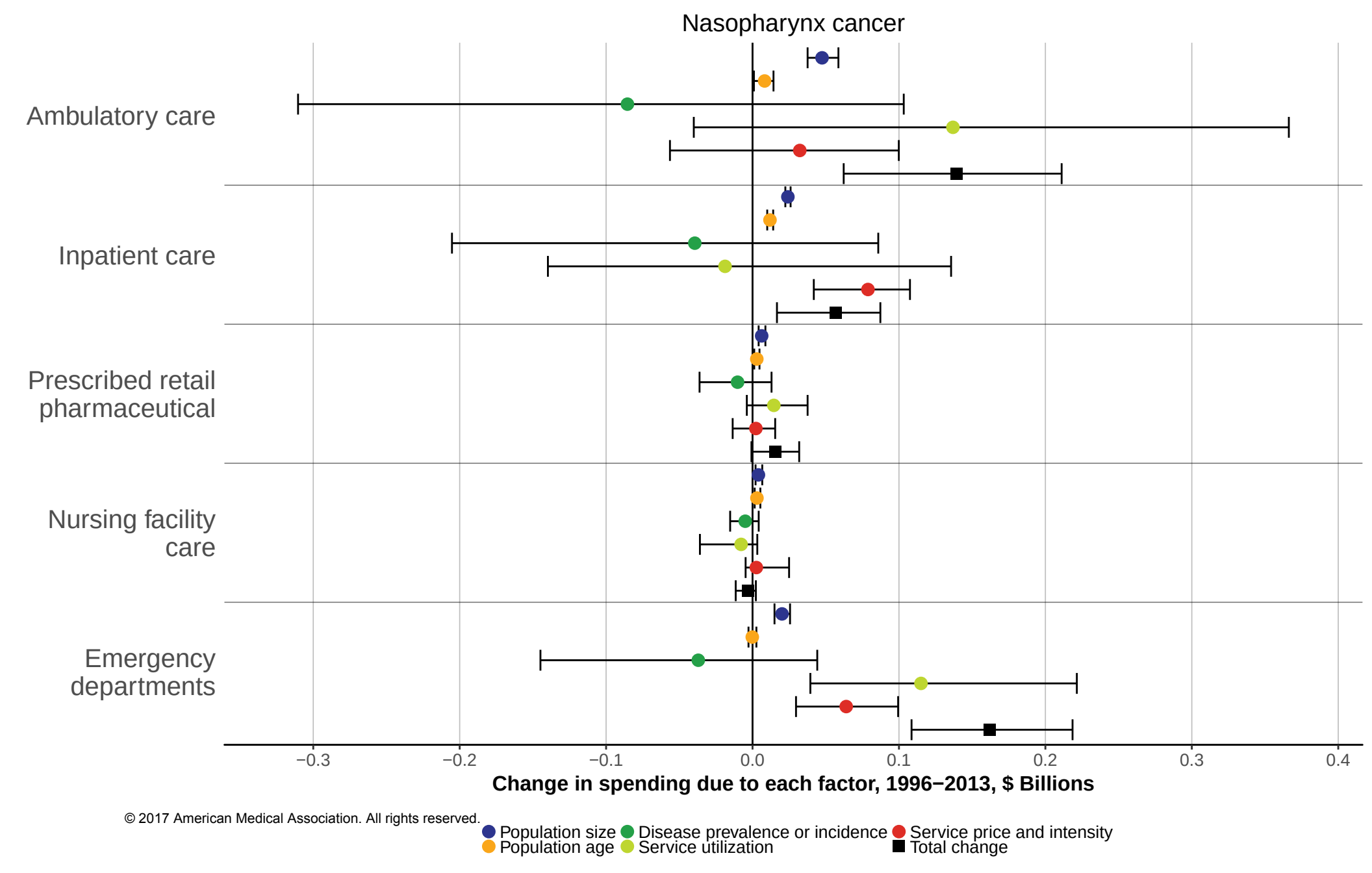


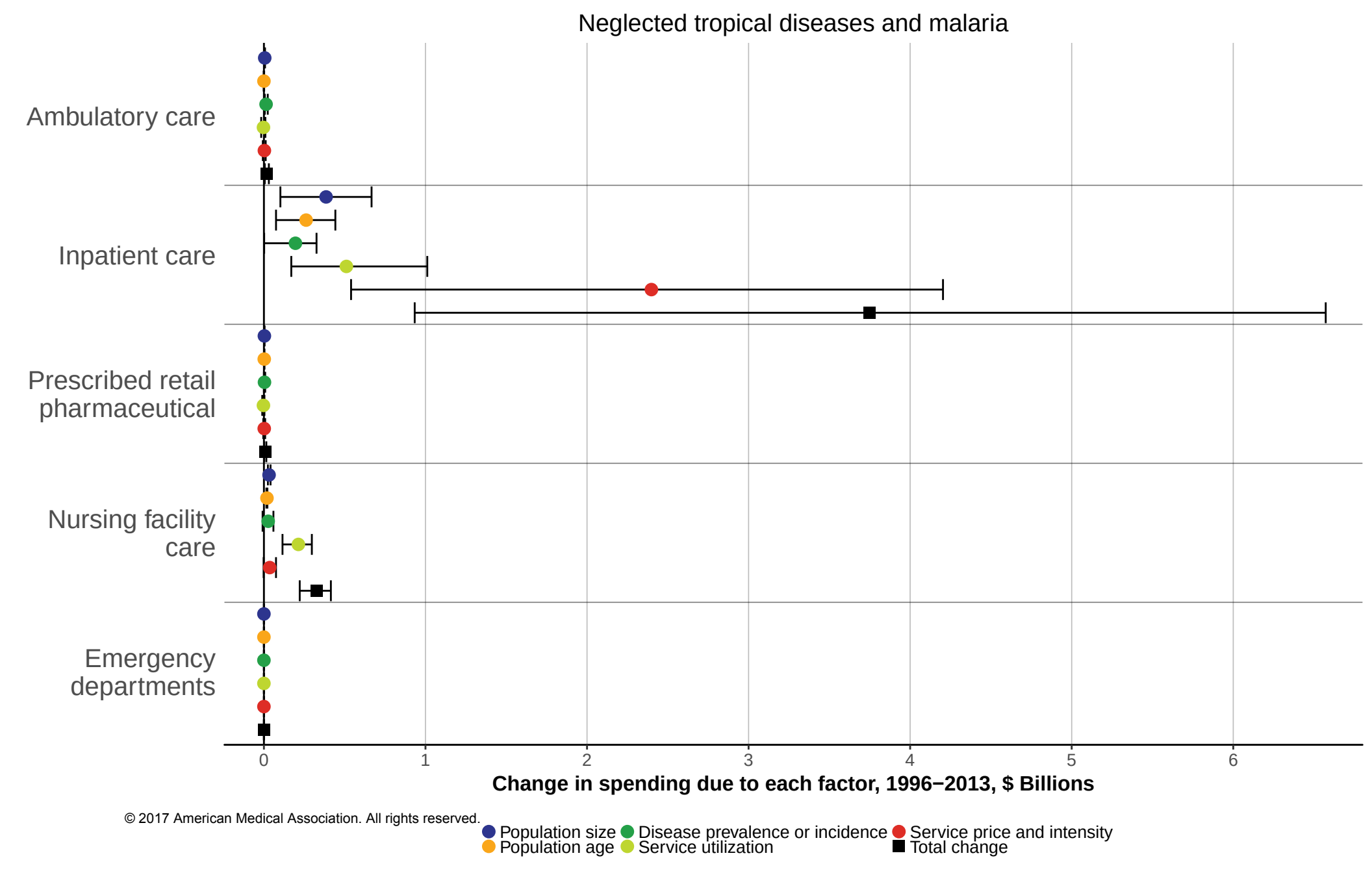


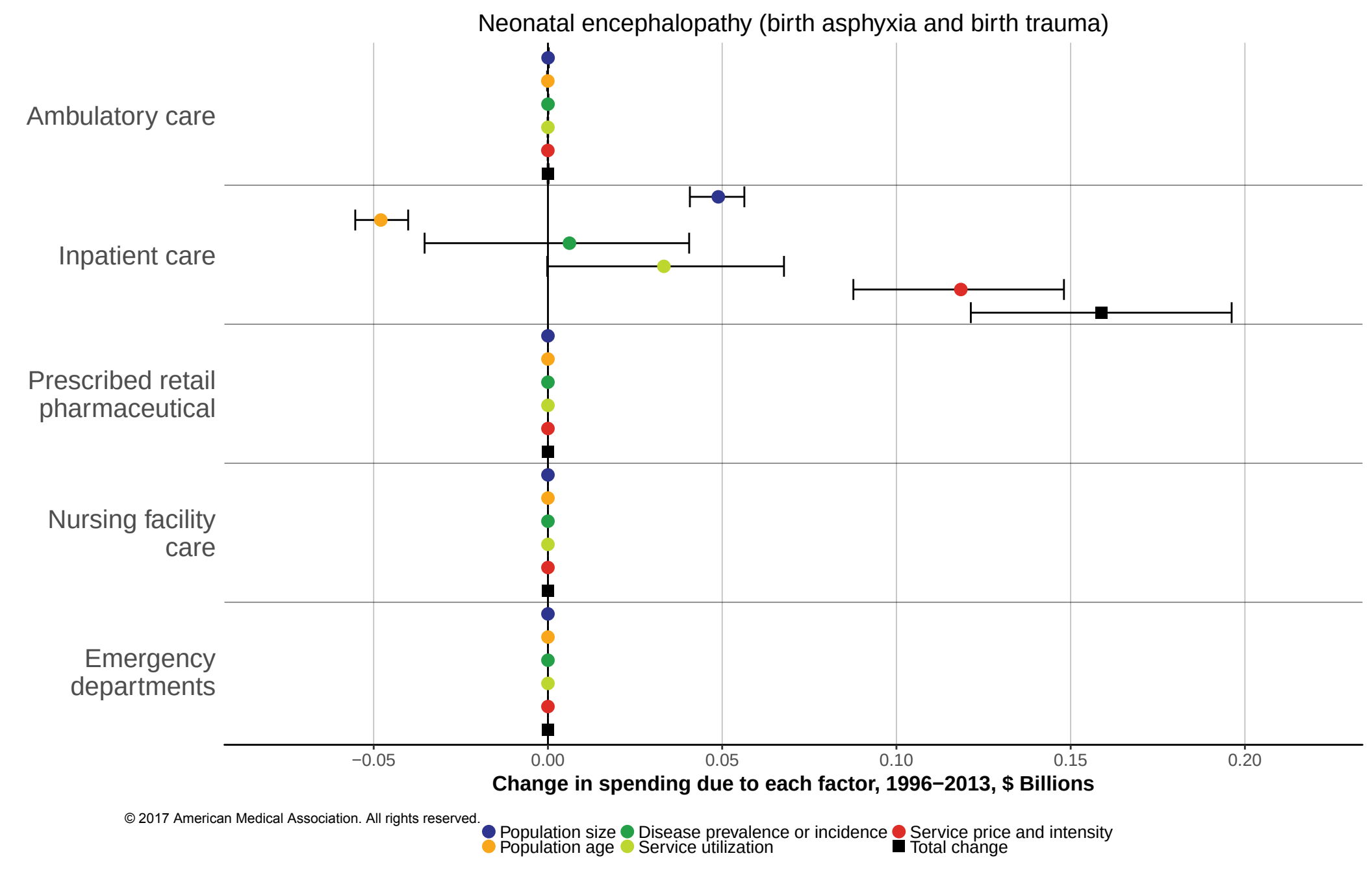




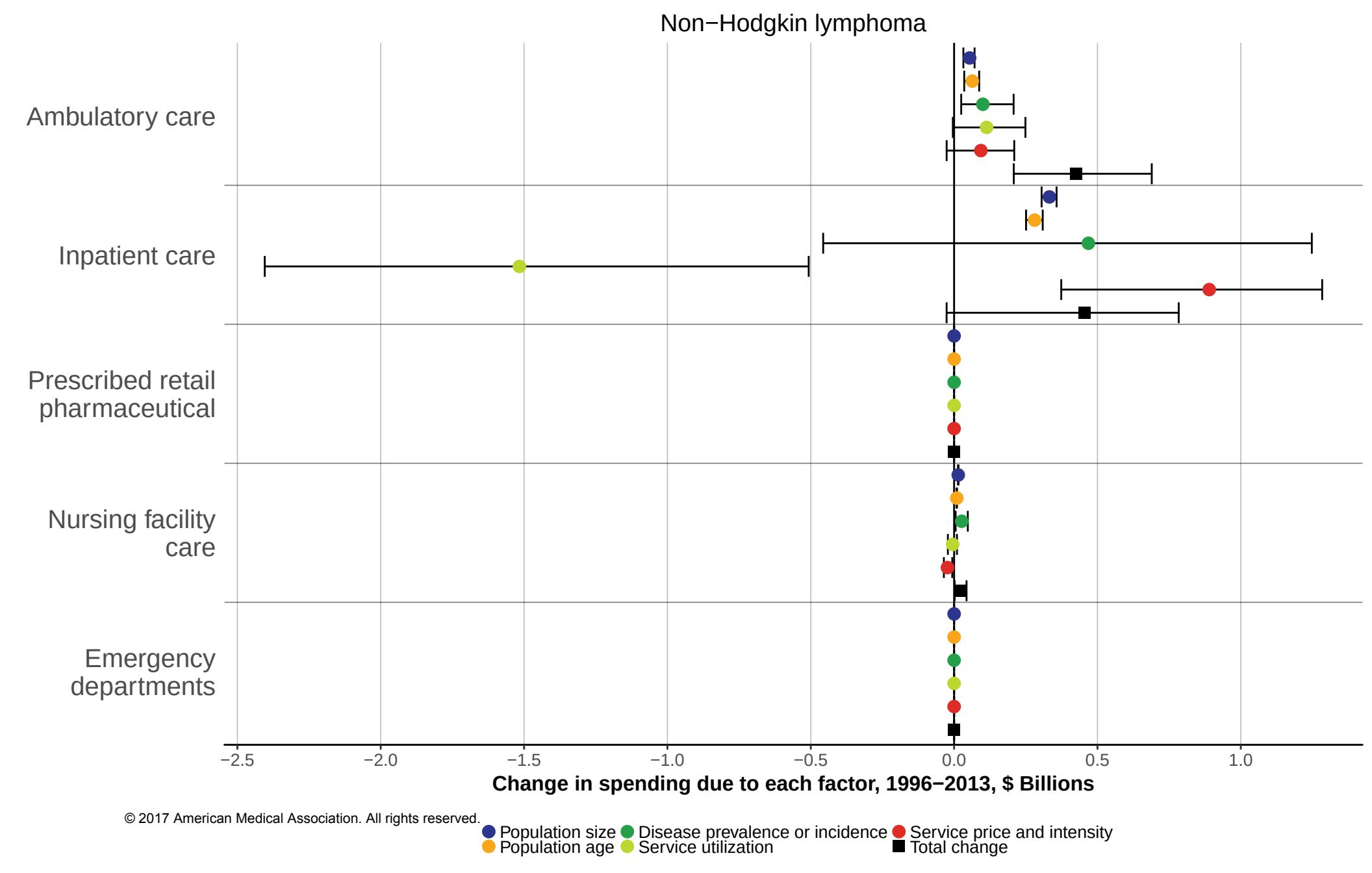
Population size
Population age
Disease prevalence or incidence
Service utilization
Service price and intensity
Total change

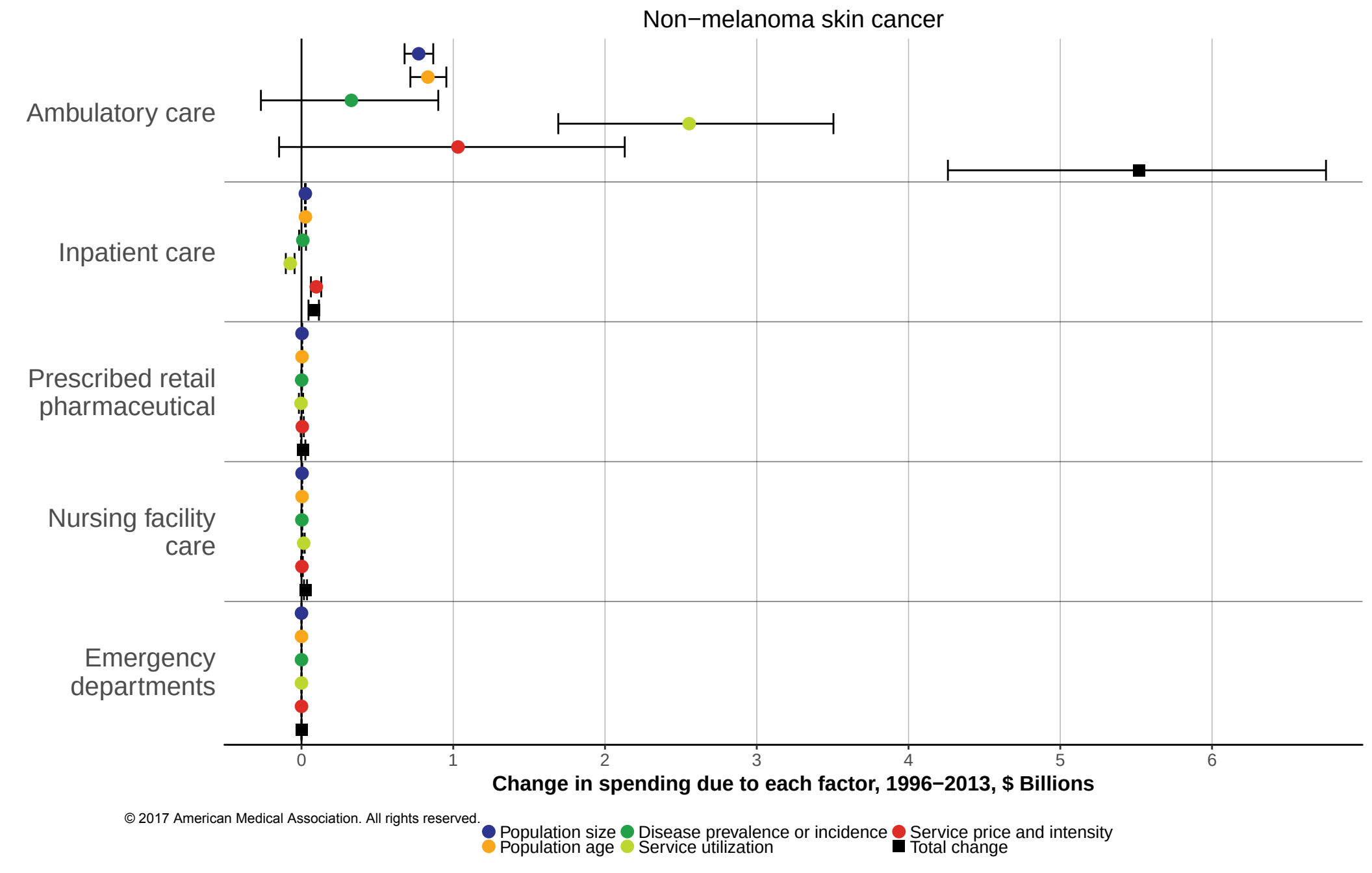




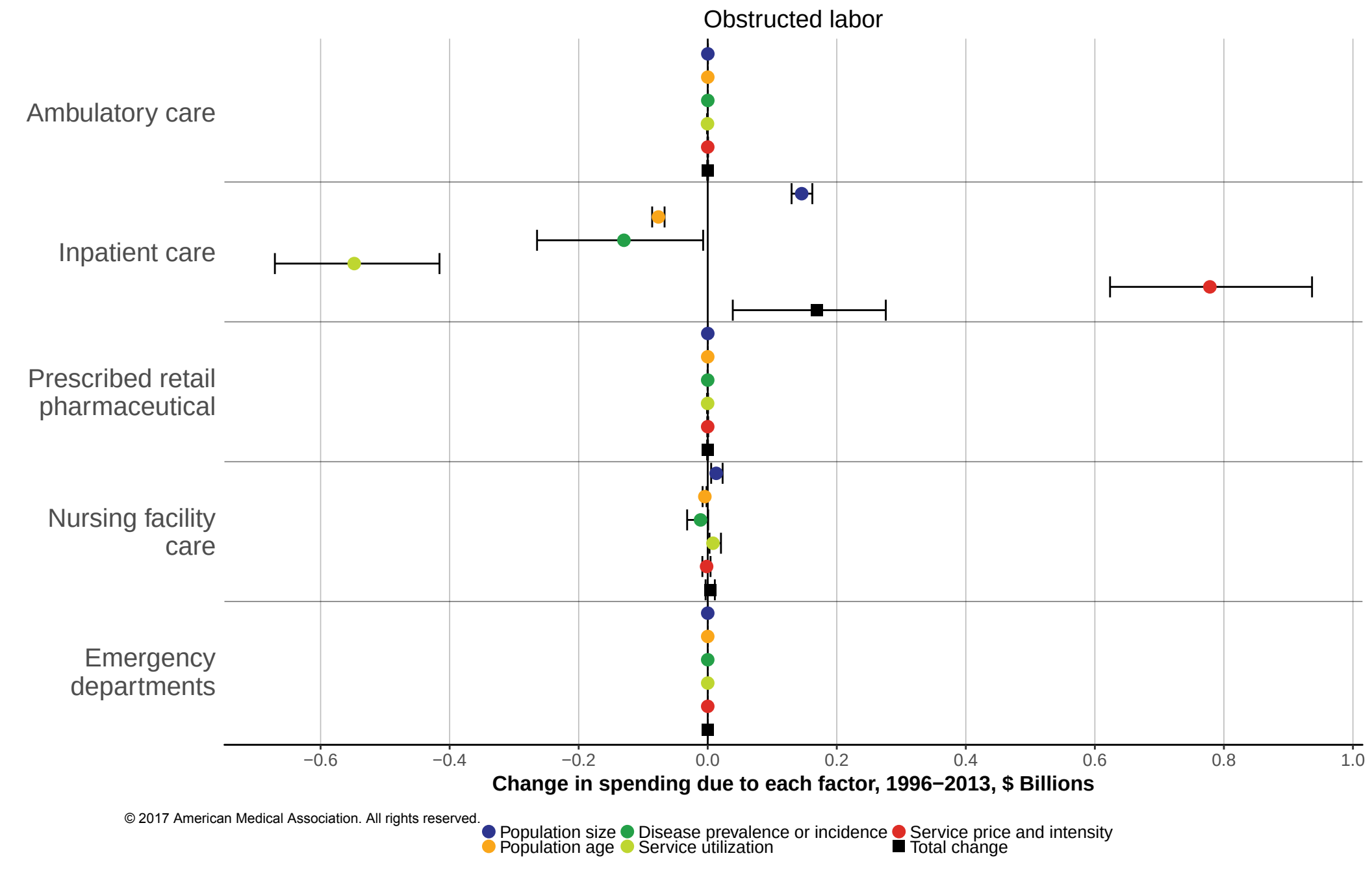


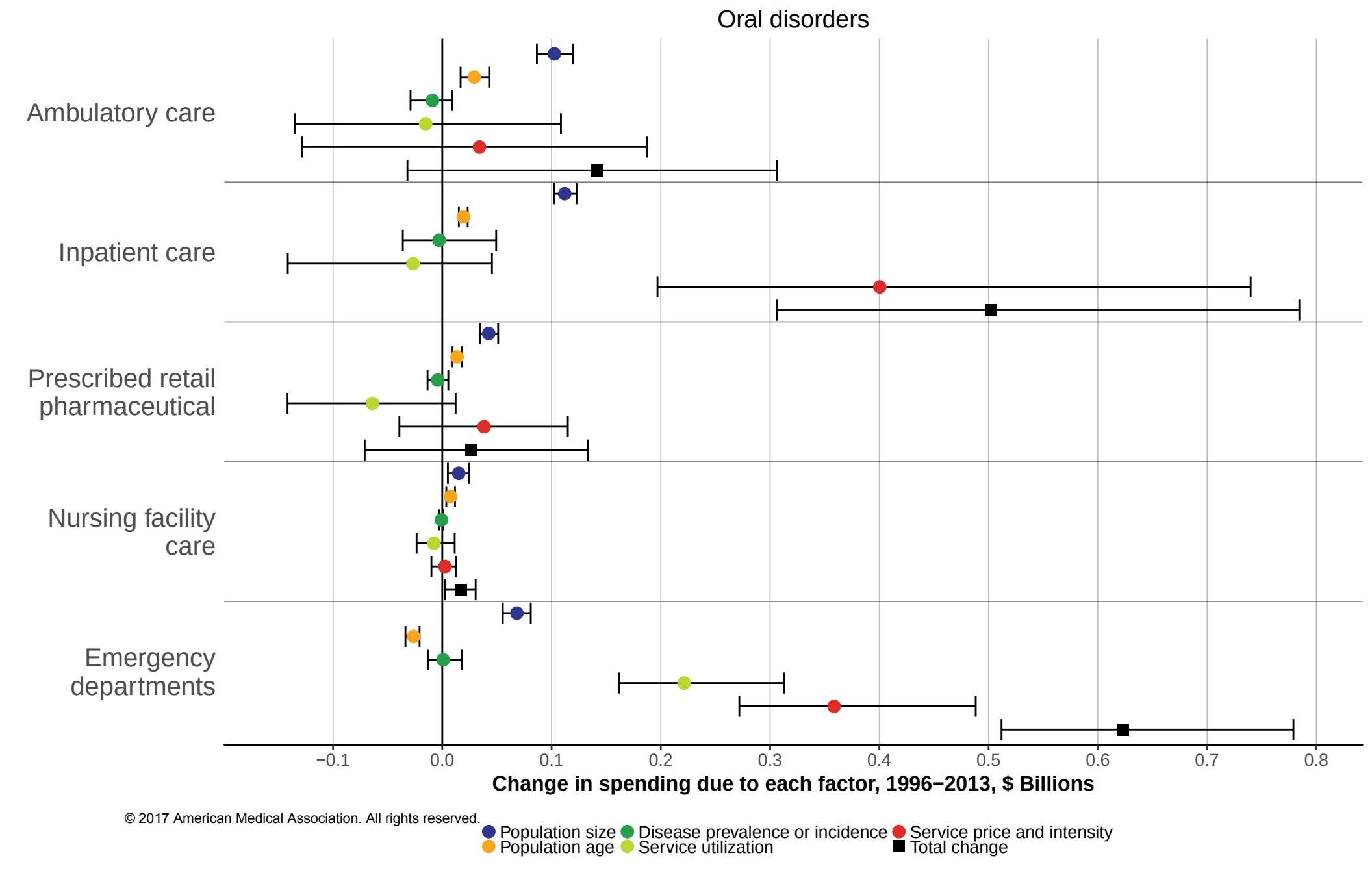
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

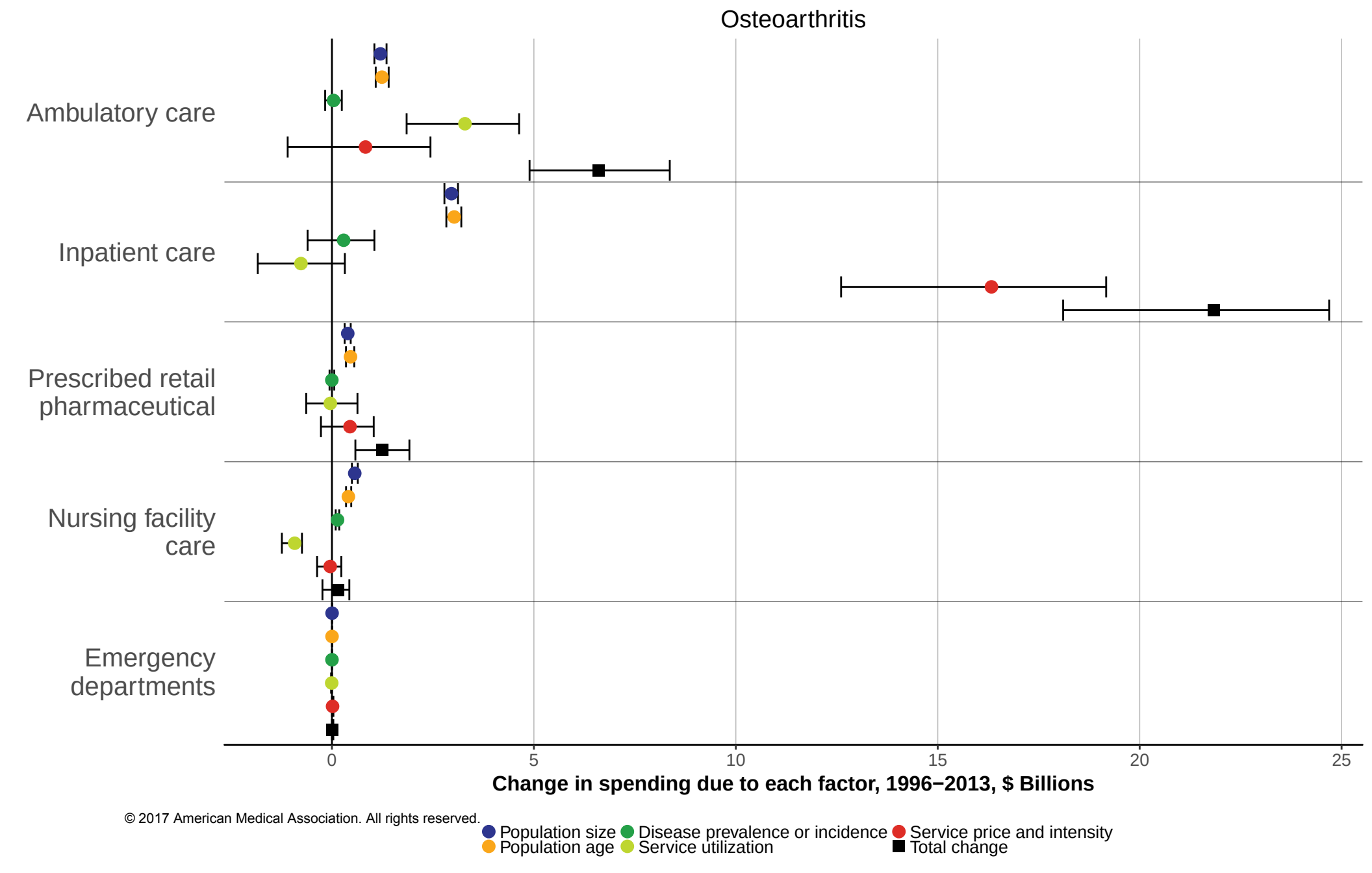


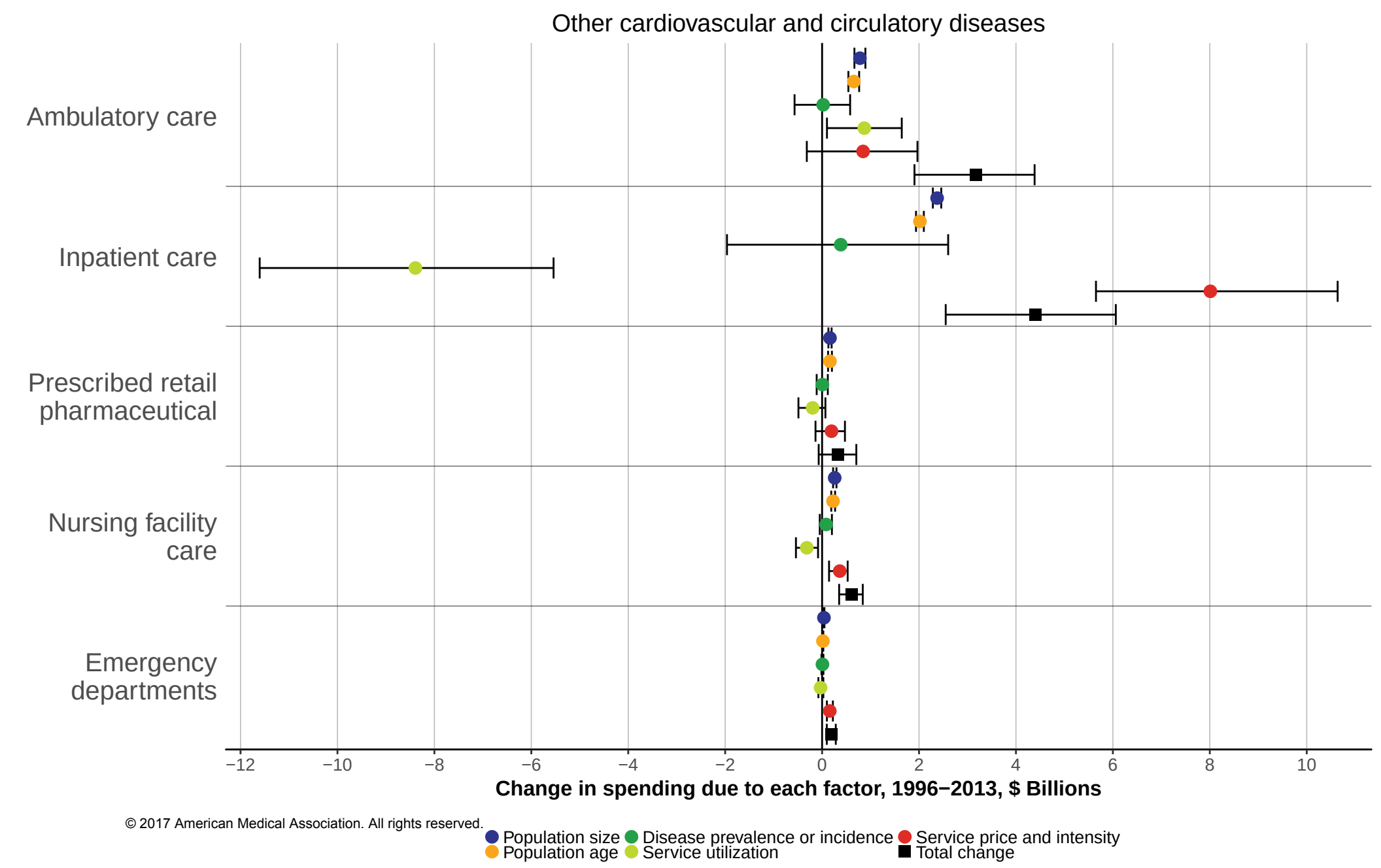


Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

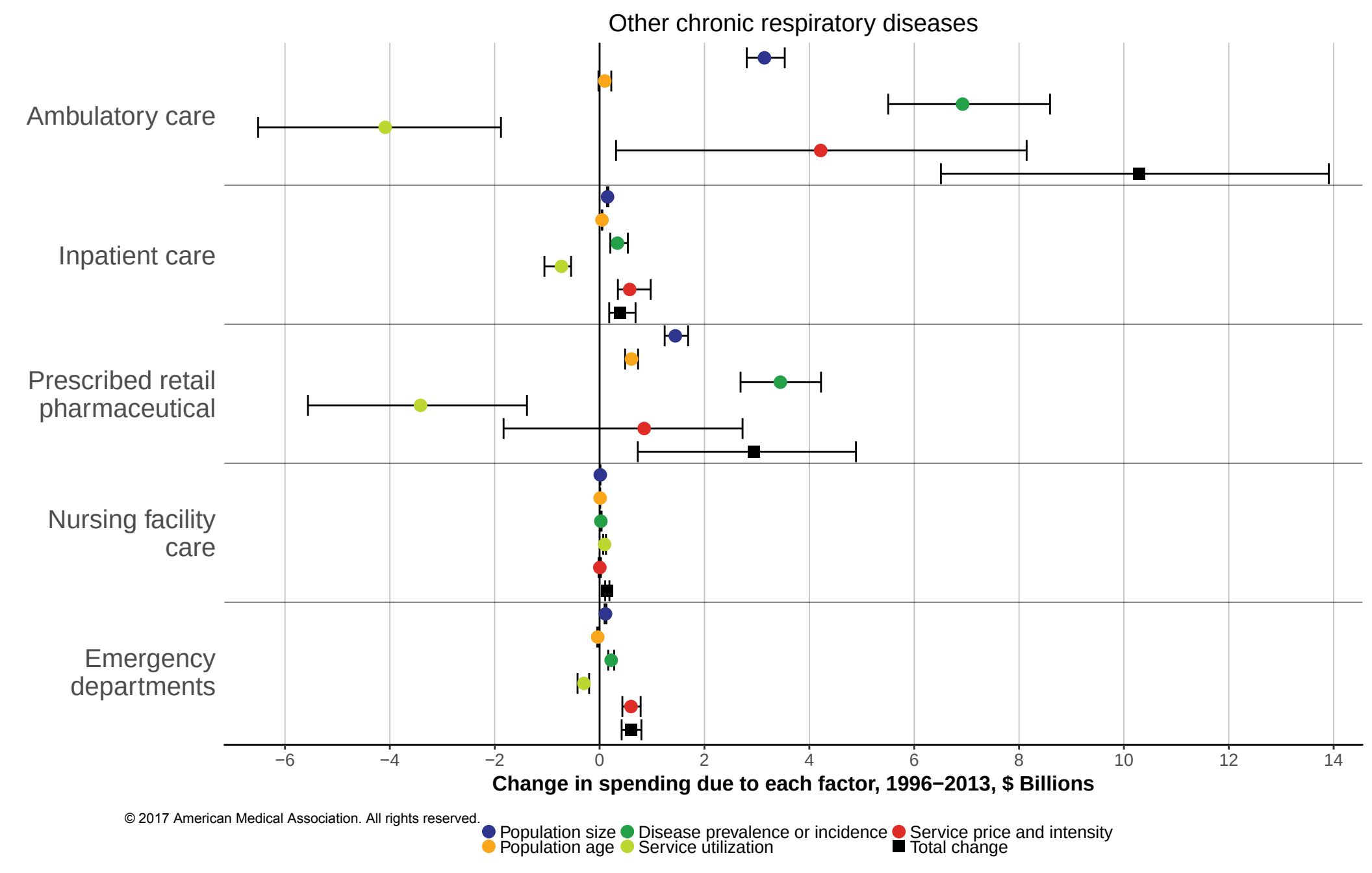


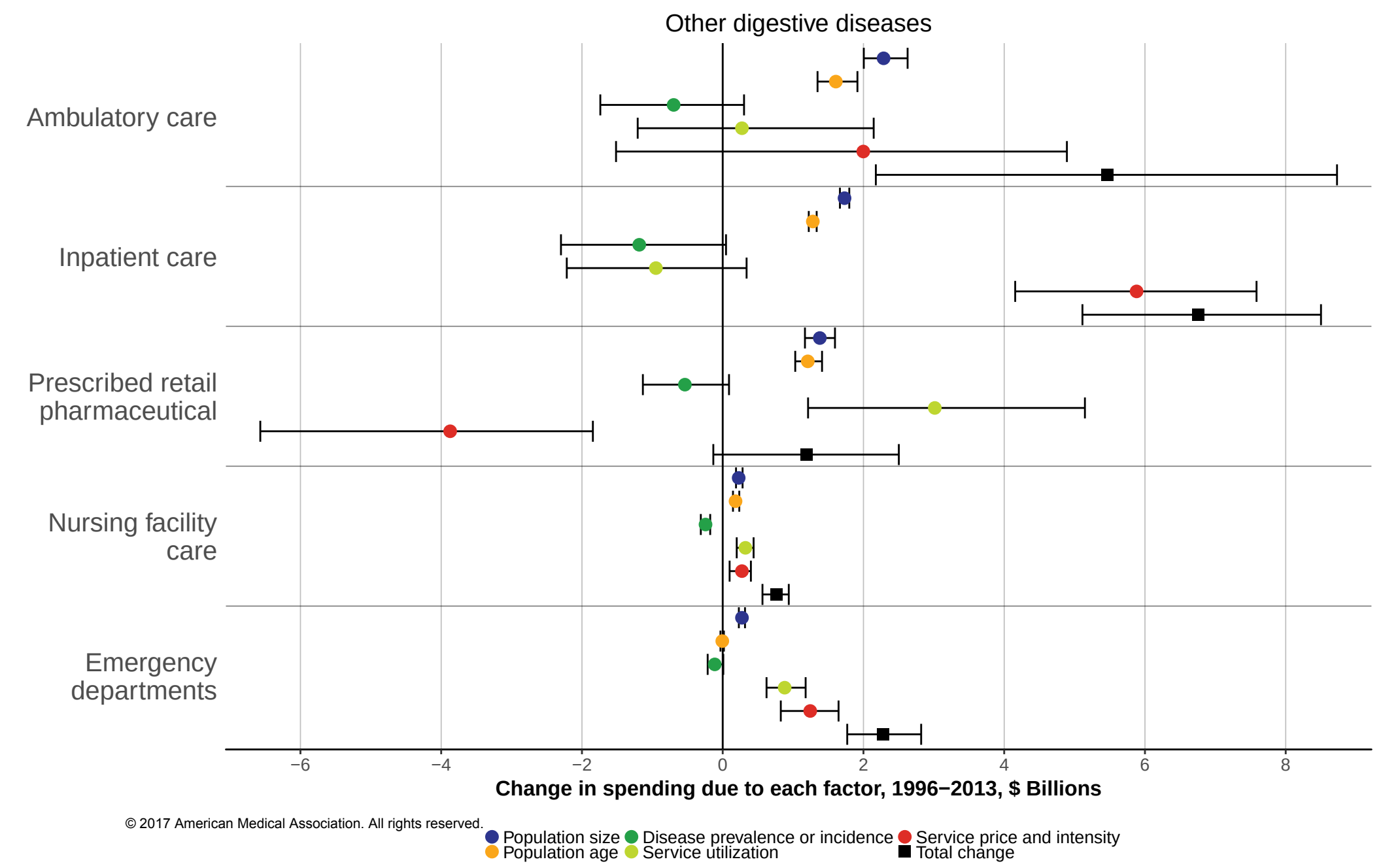


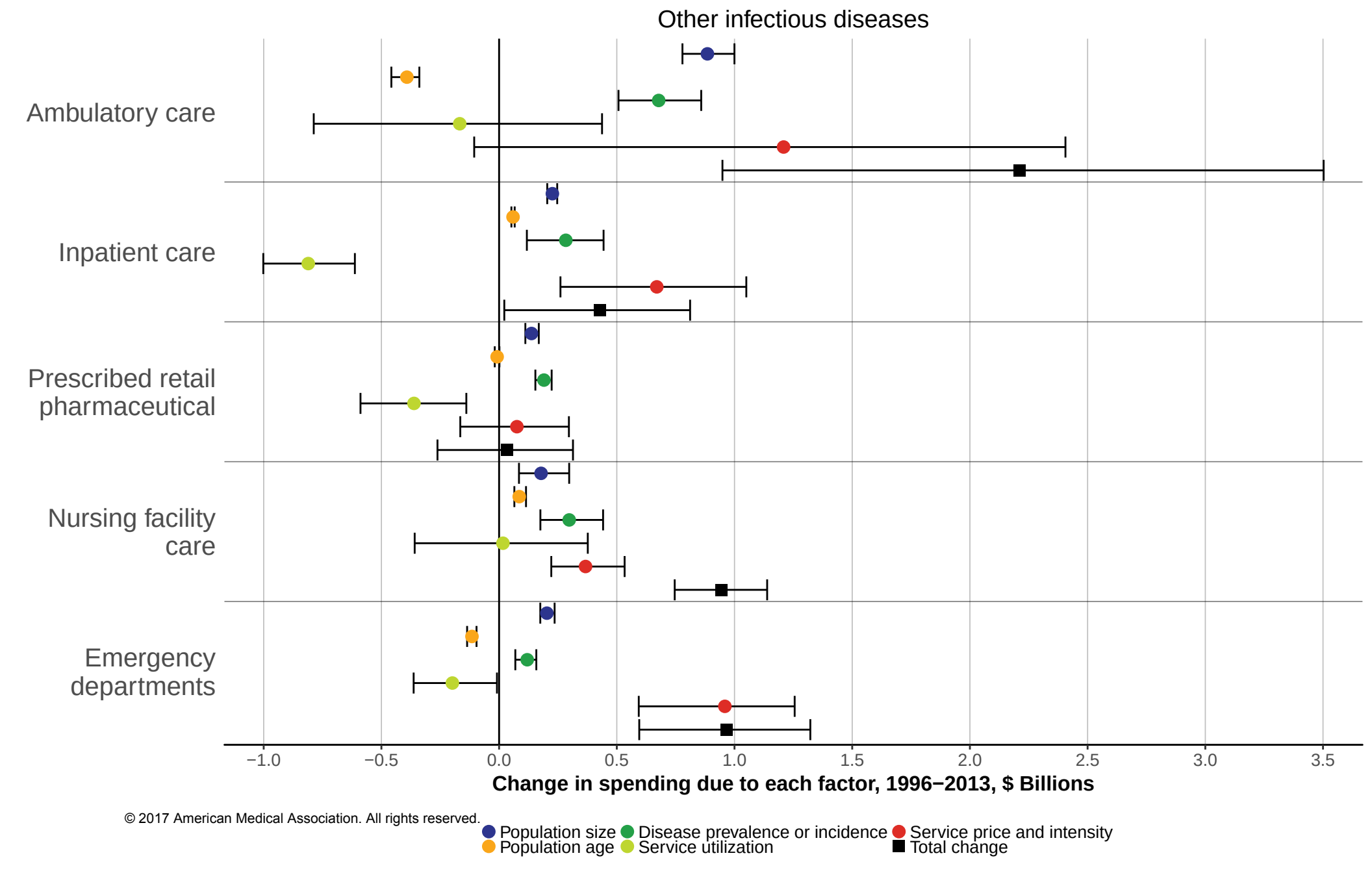


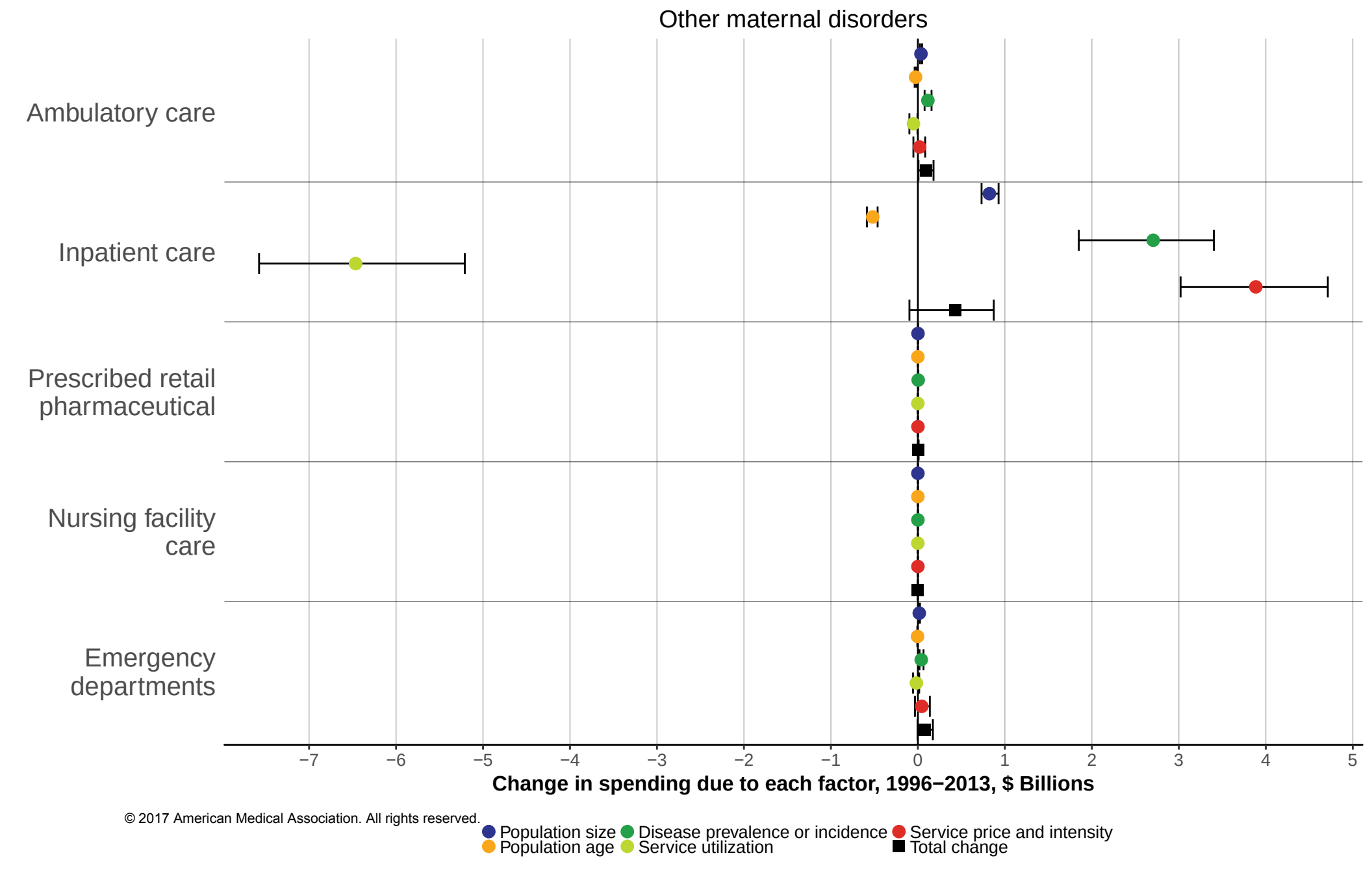


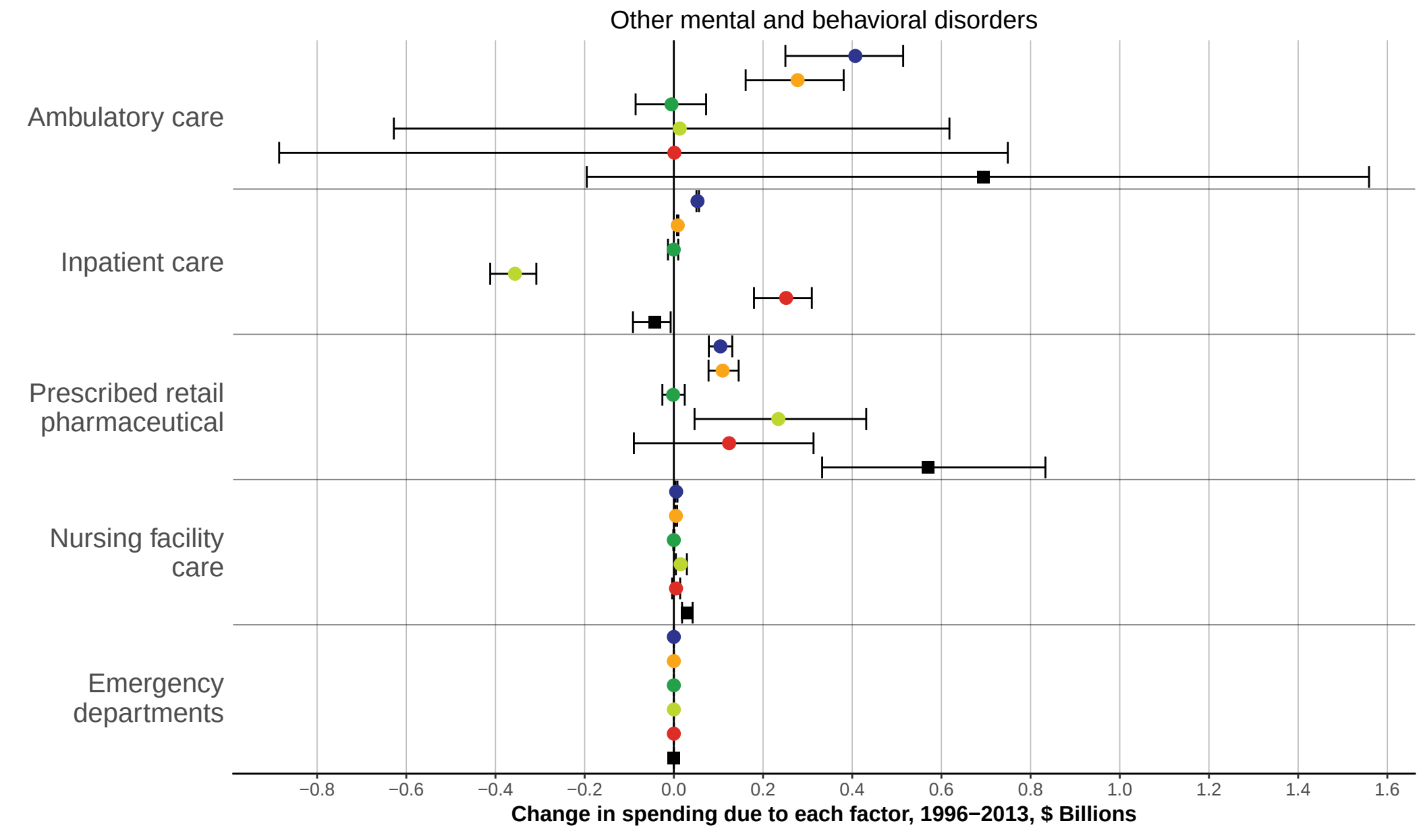
Population size
Population age
Disease prevalence or incidence
Service utilization
Service price and intensity
Total change



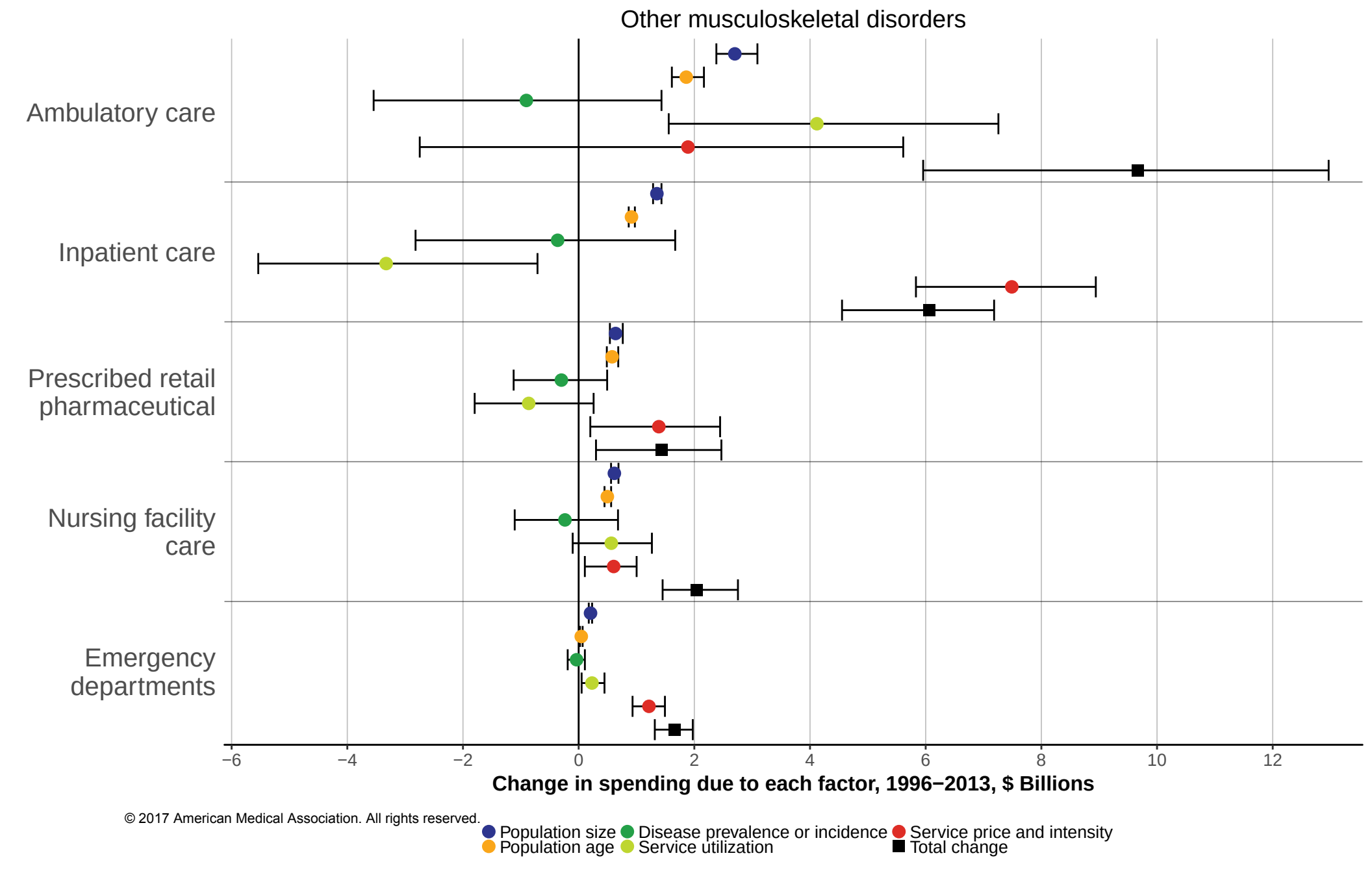


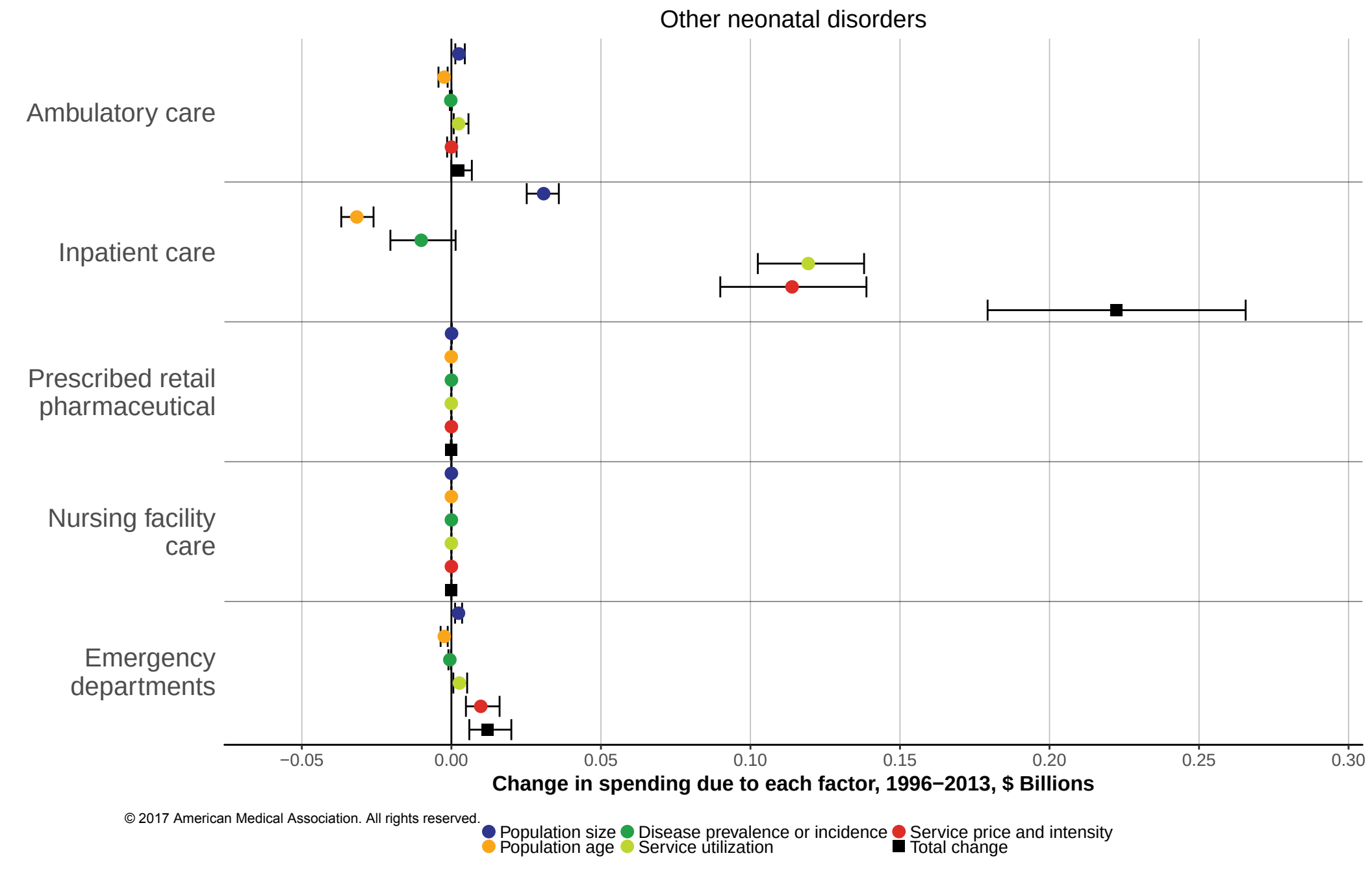




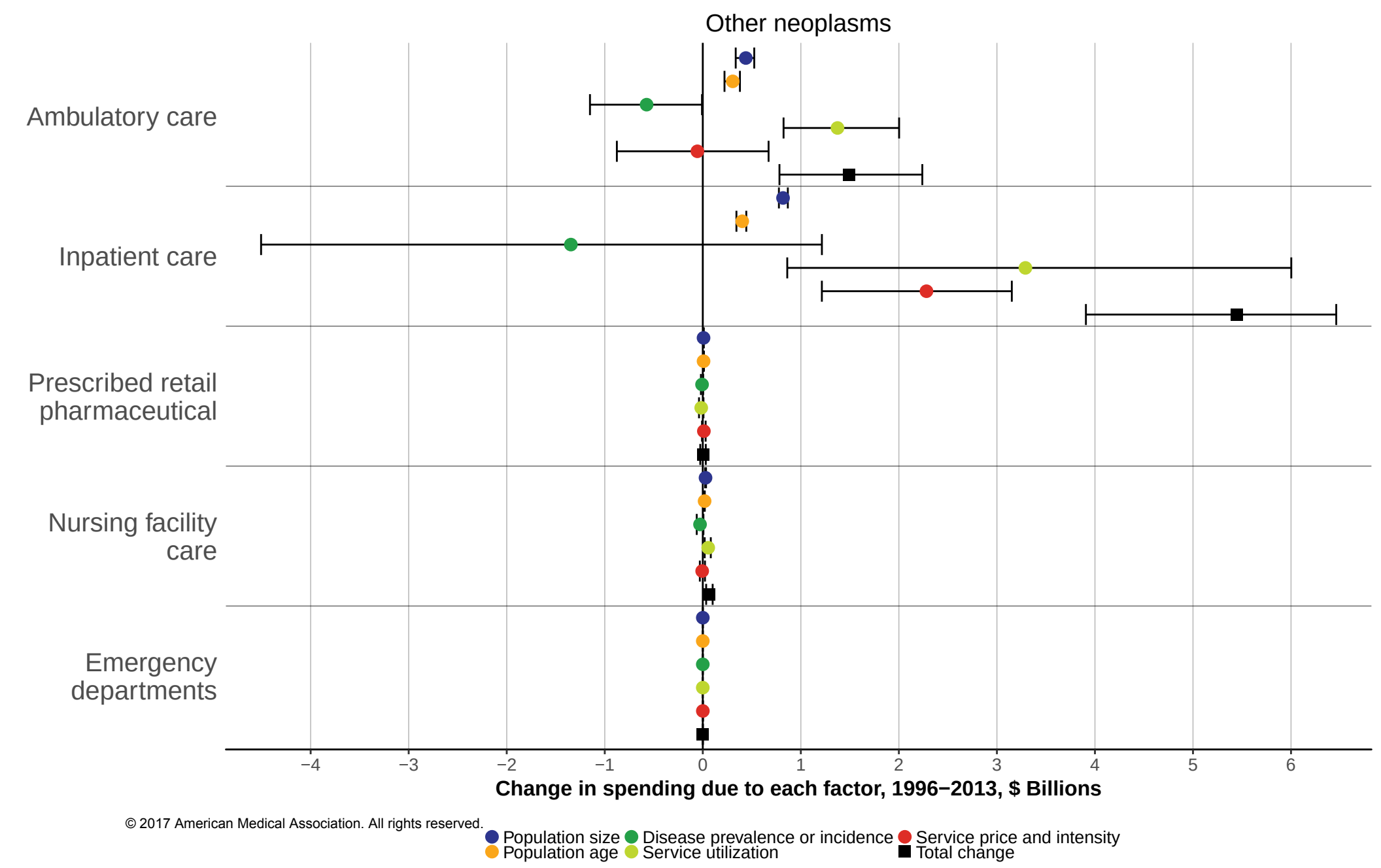


Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

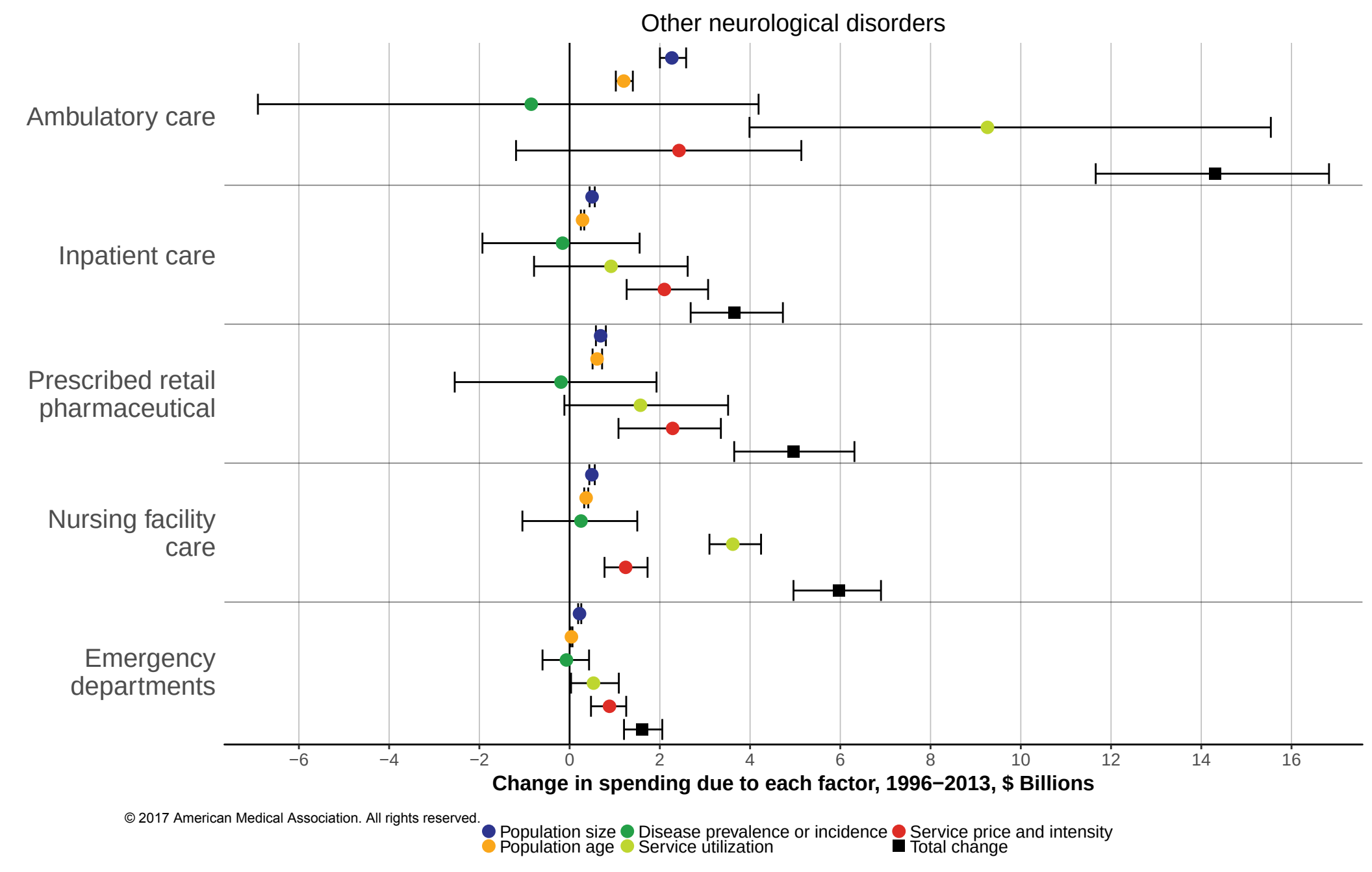




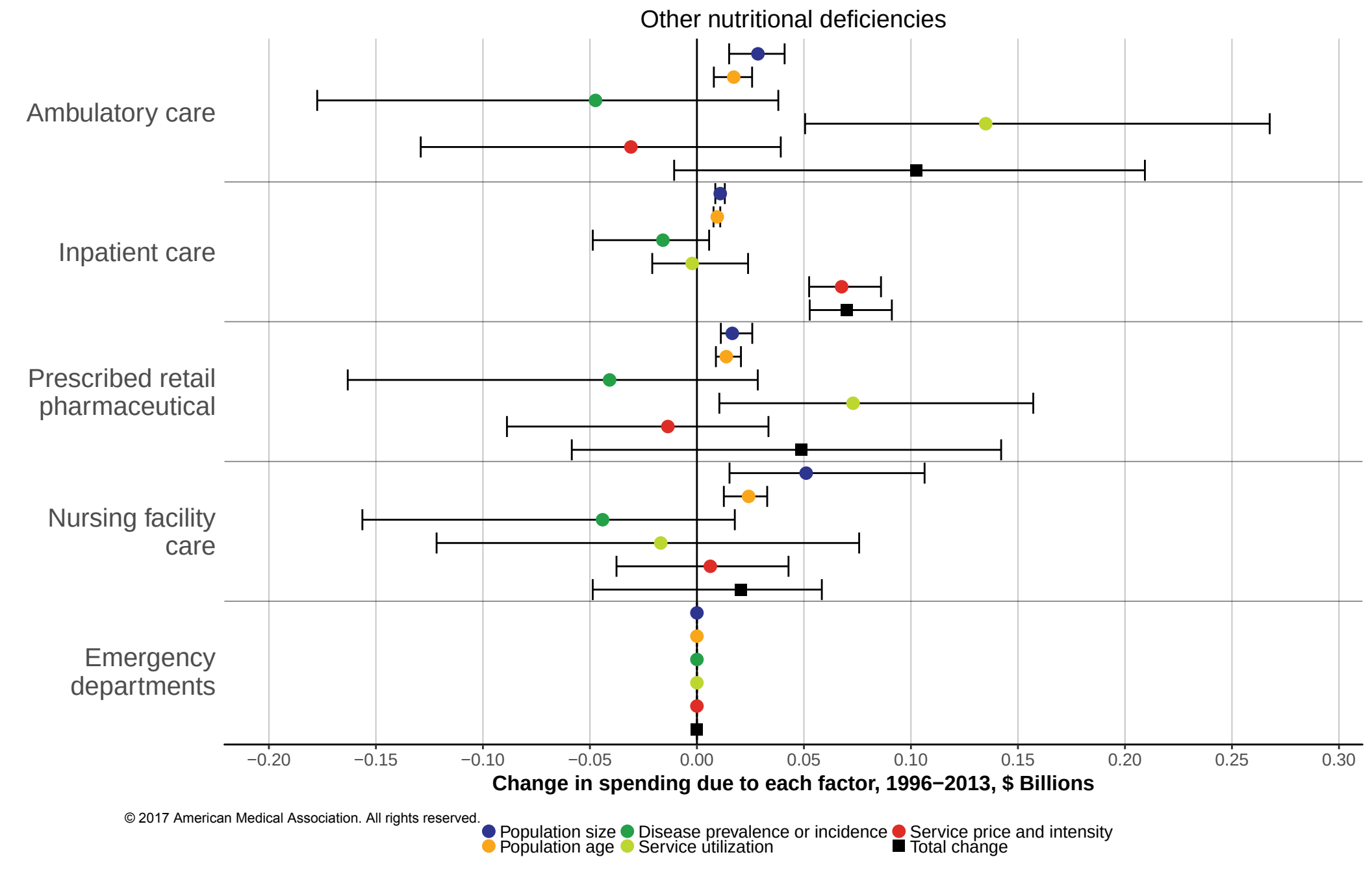
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change



Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change



Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change



Population size
Disease prevalence or incidence
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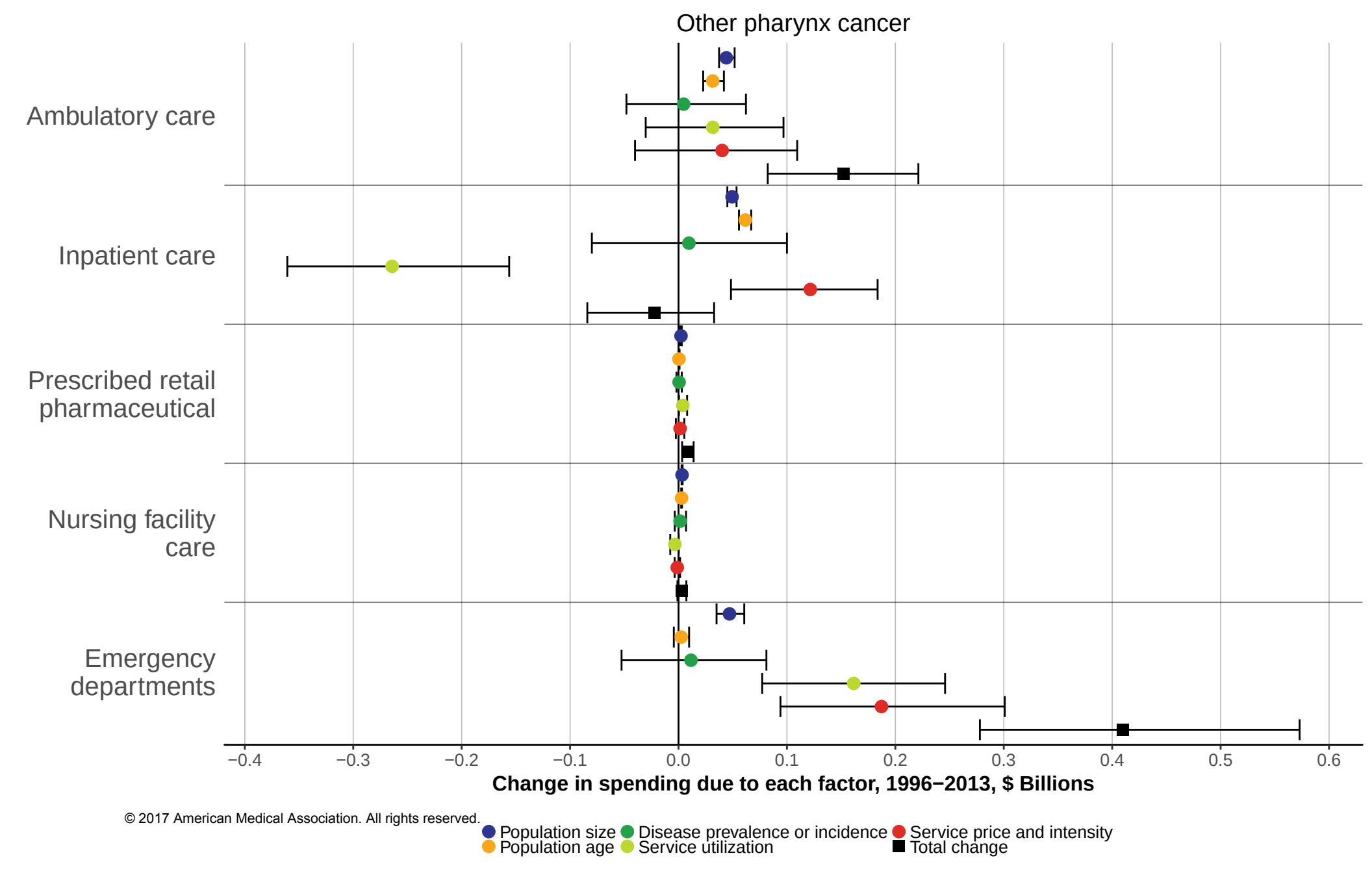
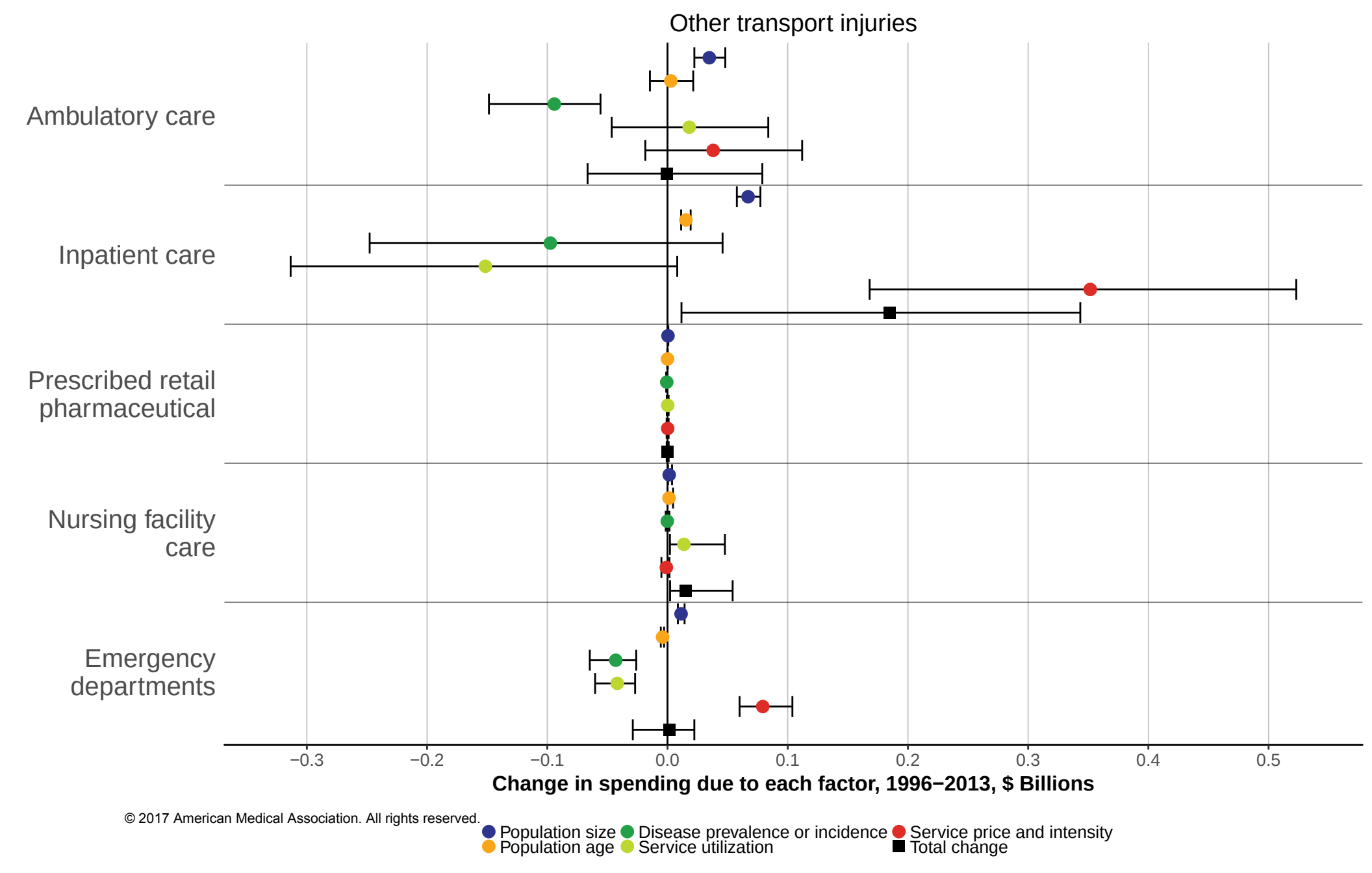
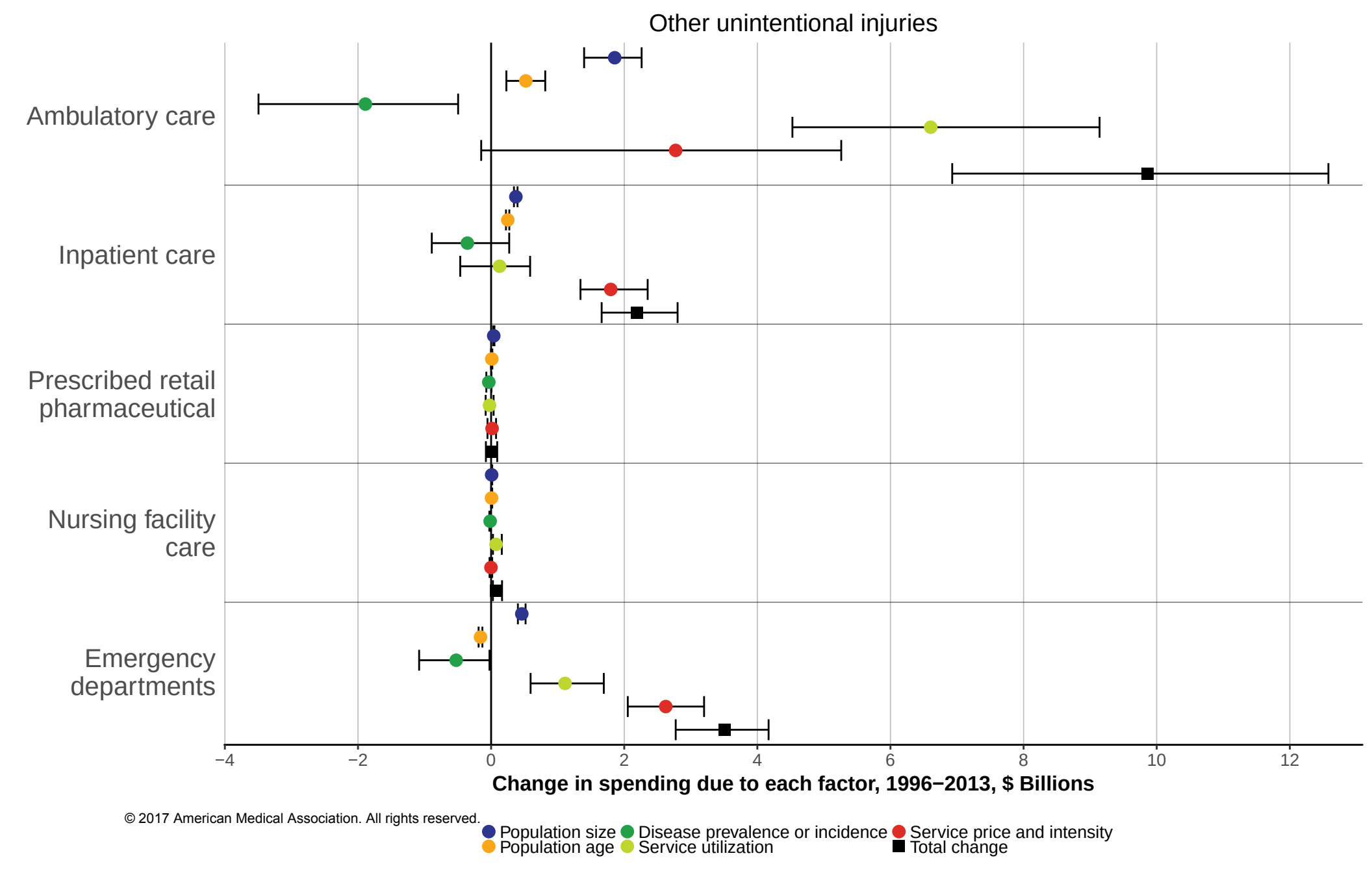
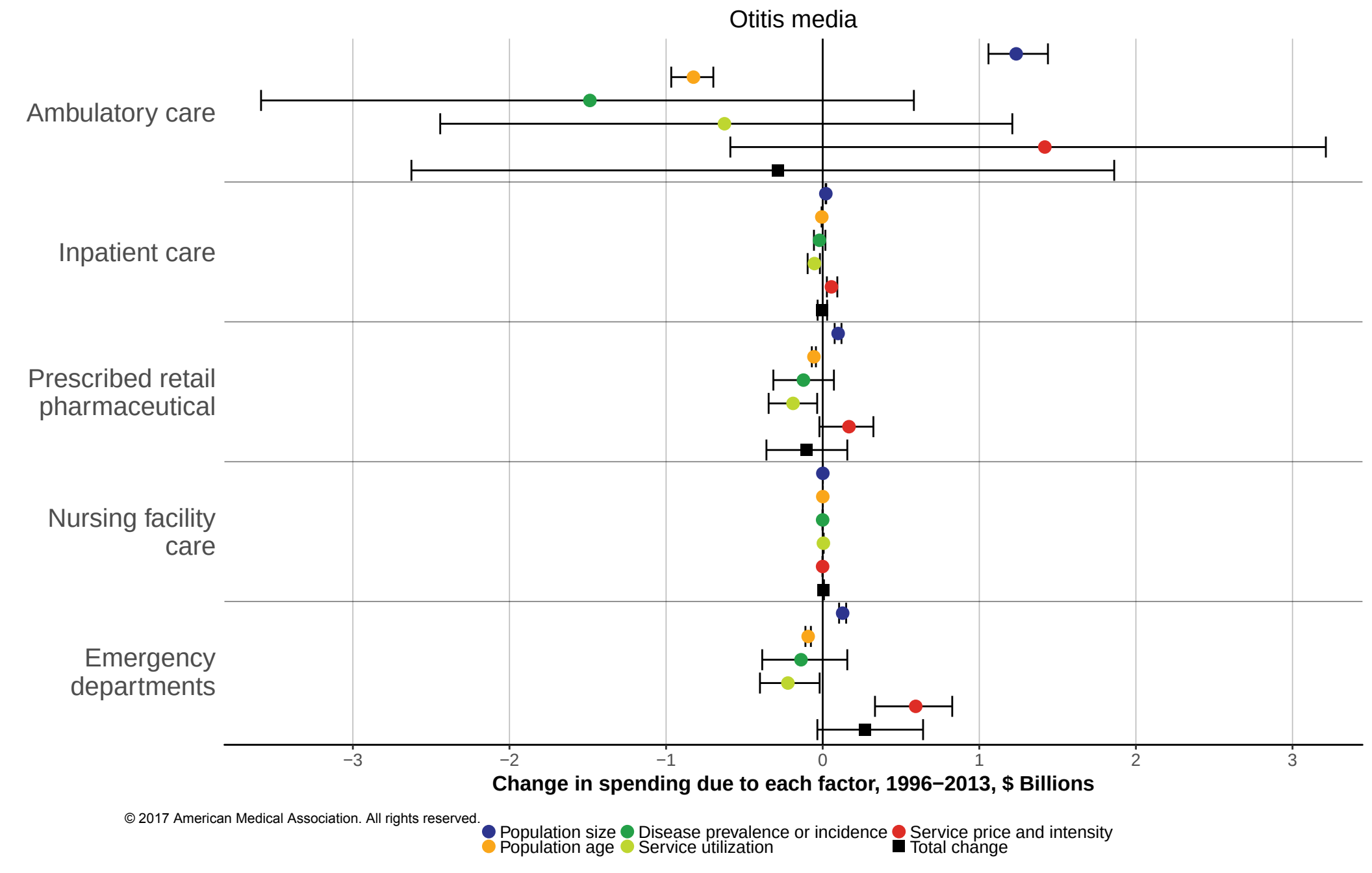
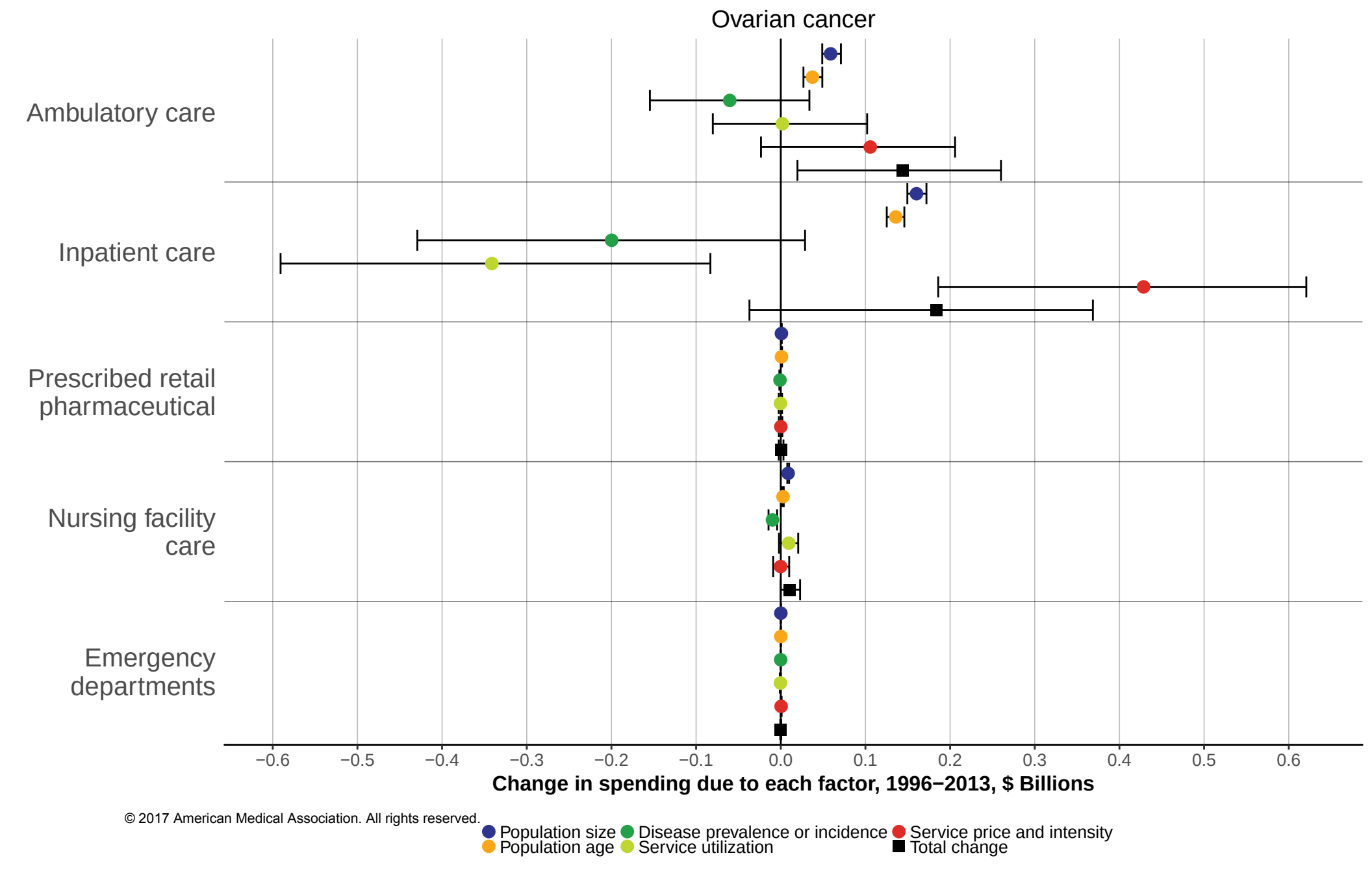
Service utilization
Total change

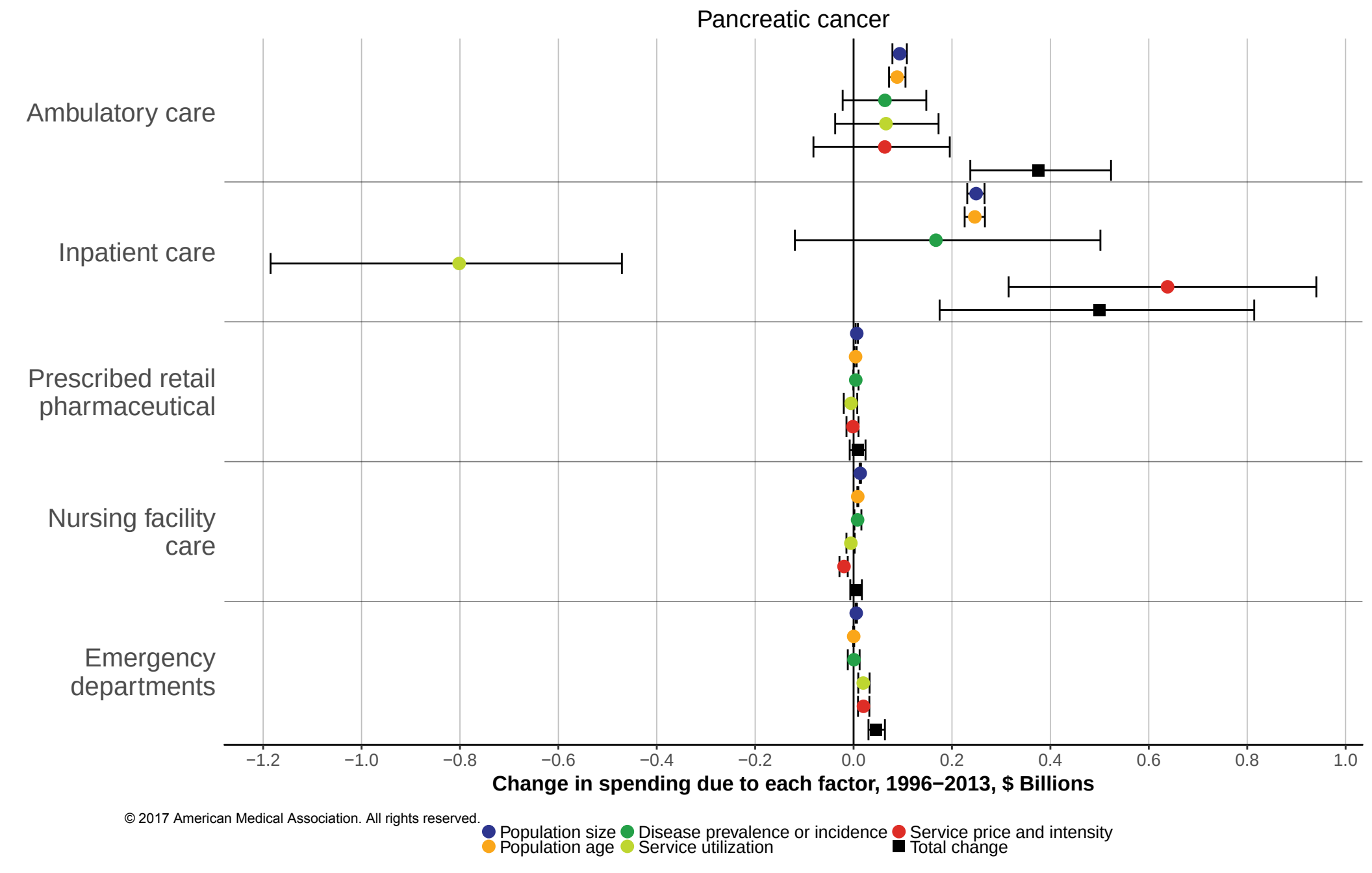


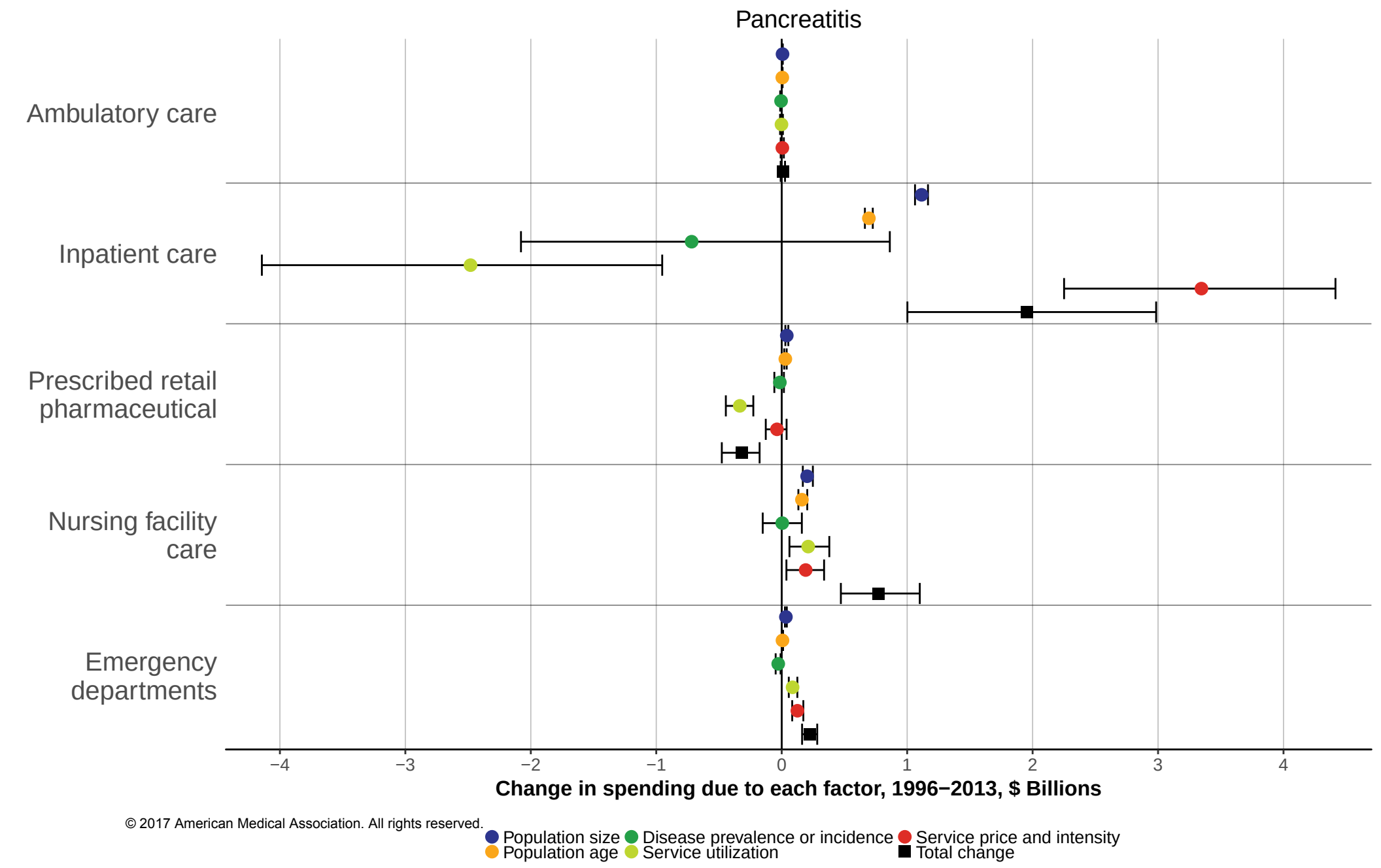




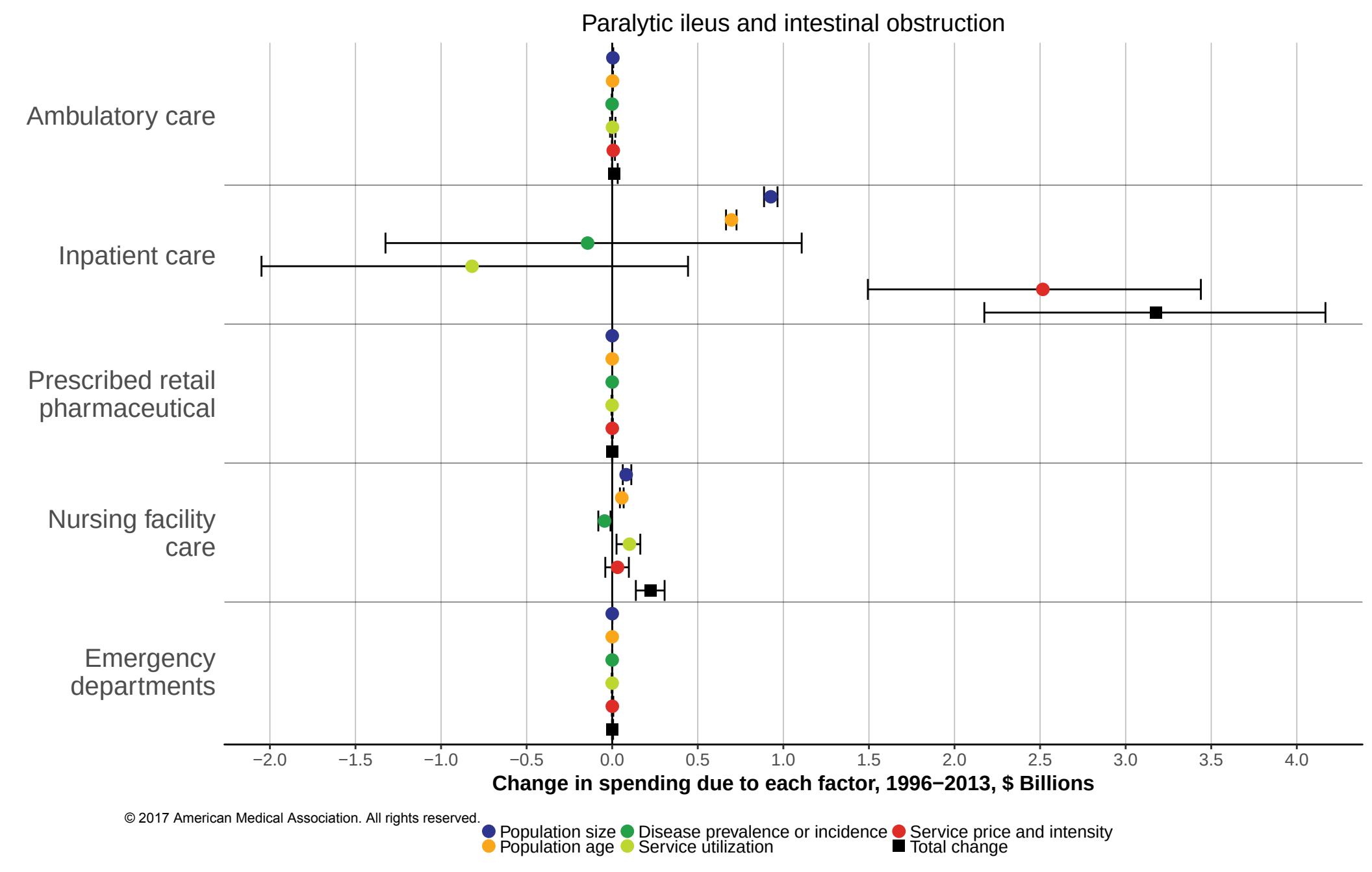


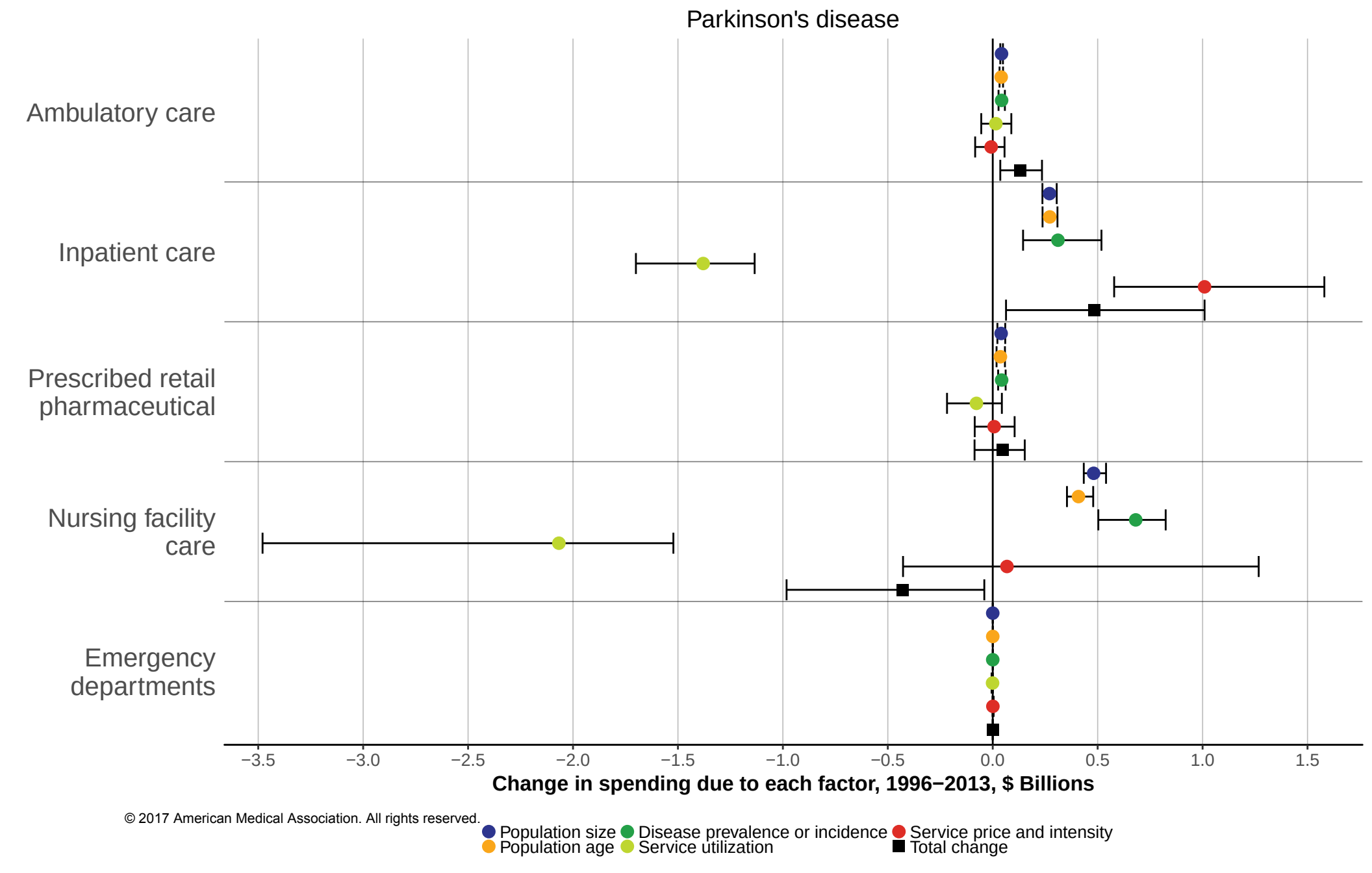


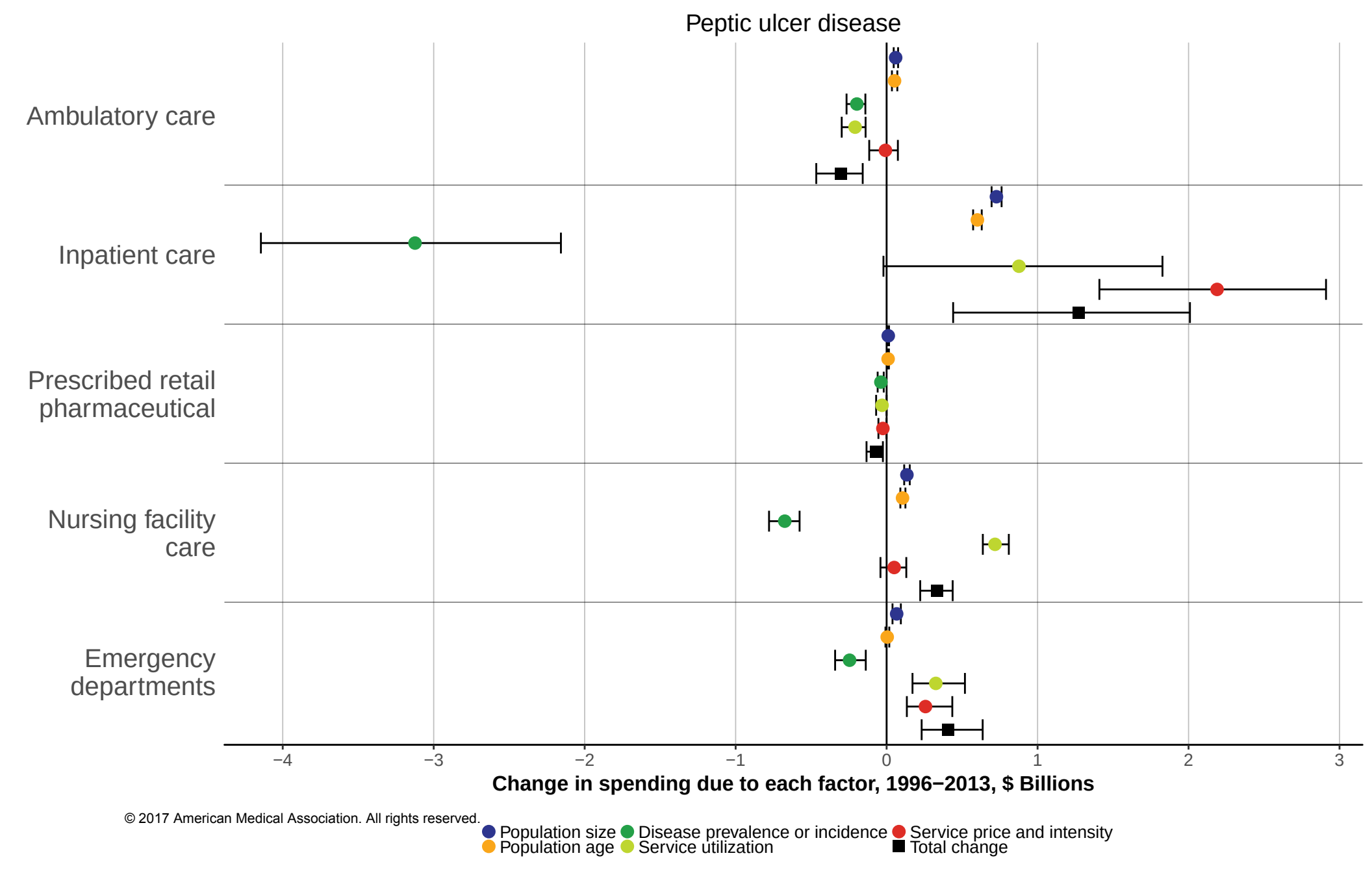




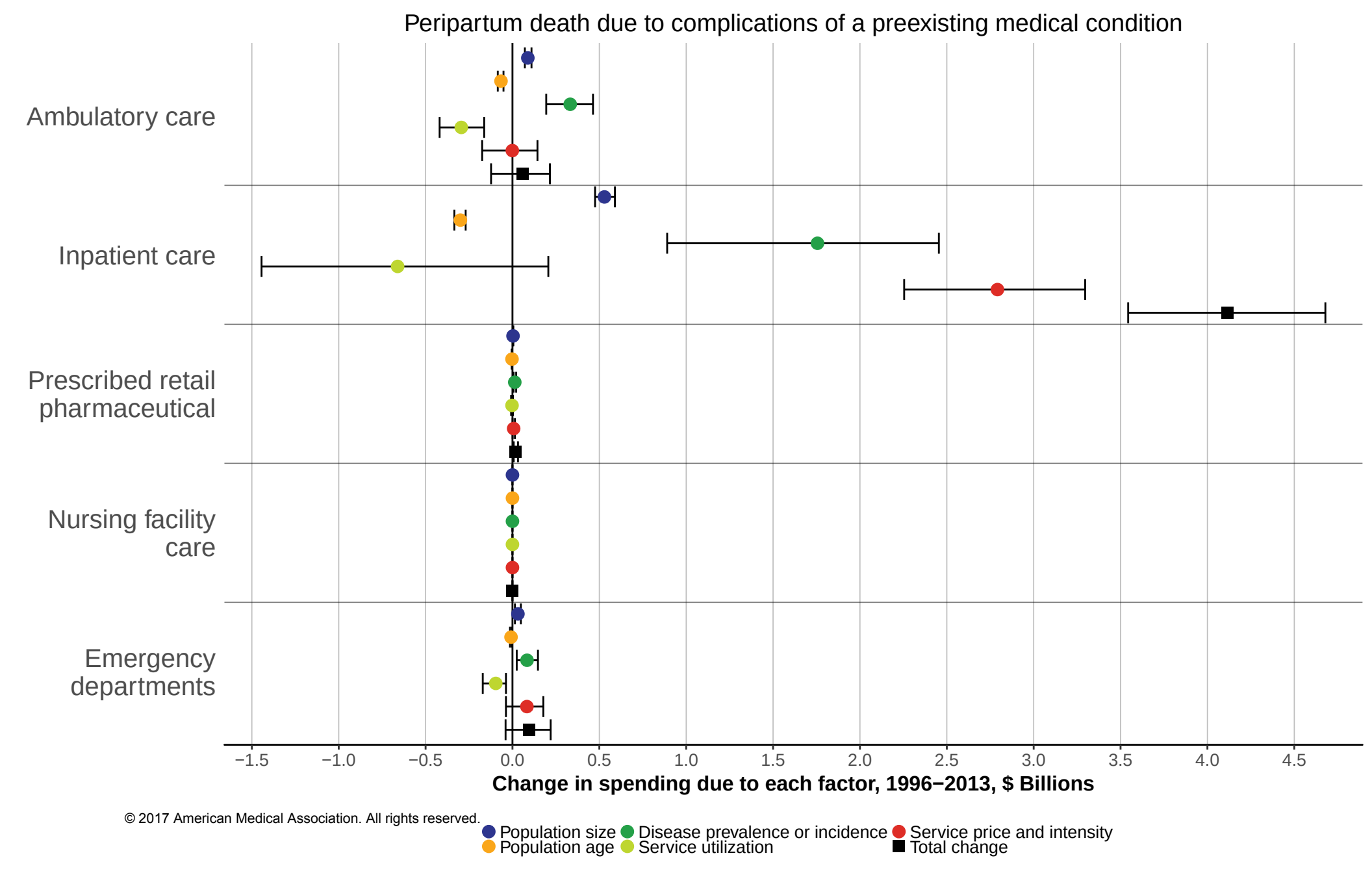
Population size
Population age
Disease prevalence or incidence
Service utilization
Service price and intensity
Total change

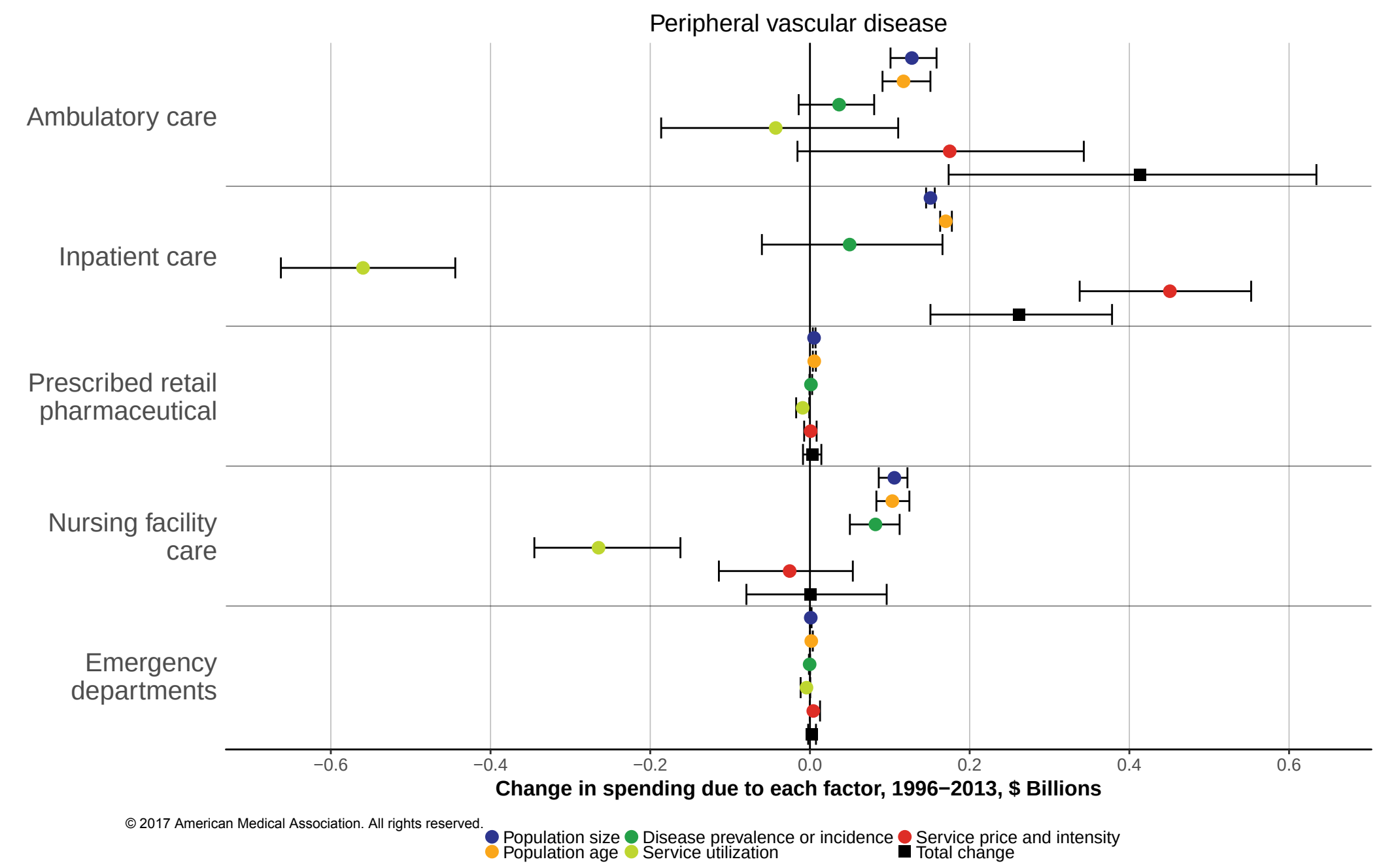


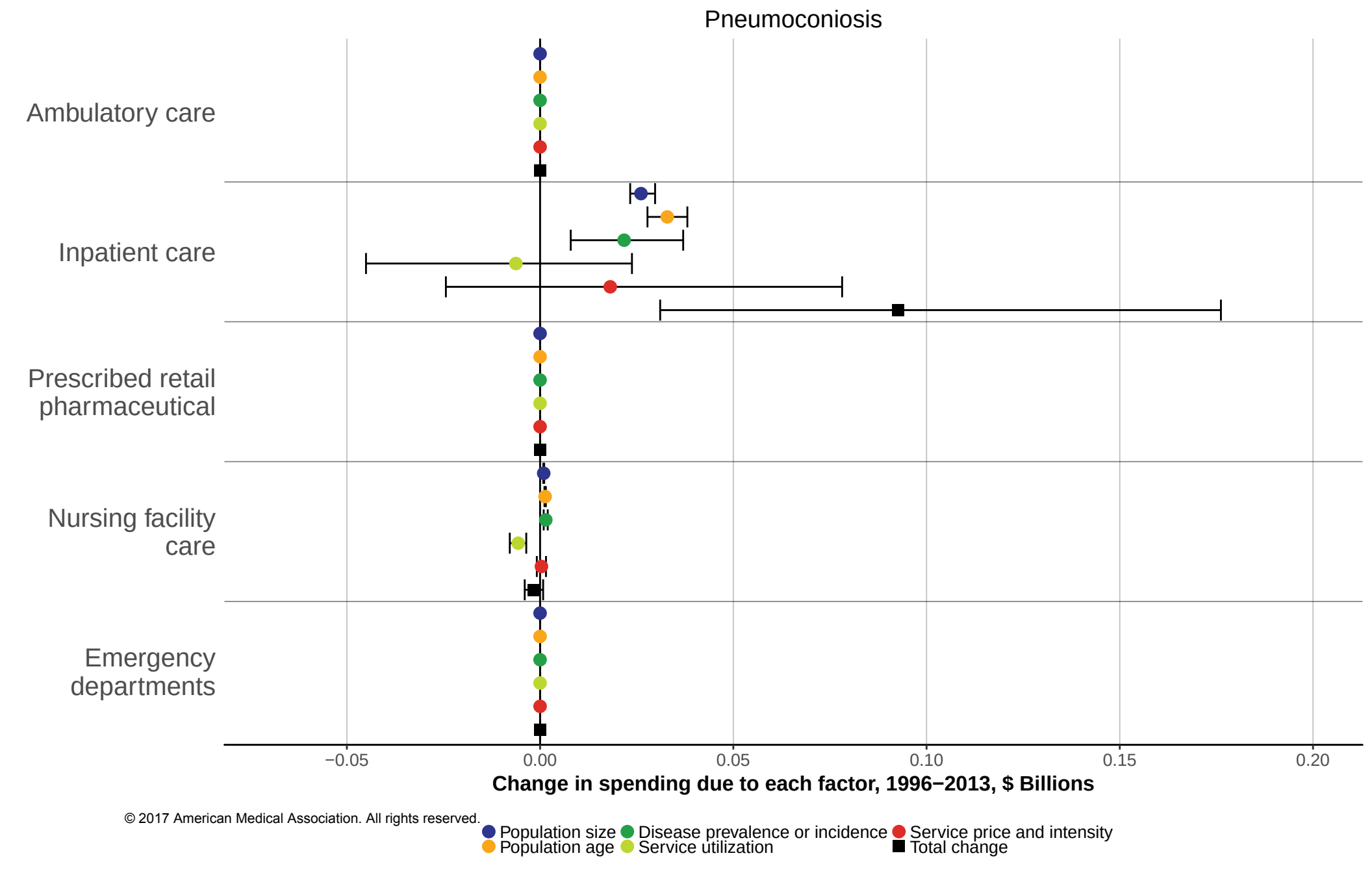


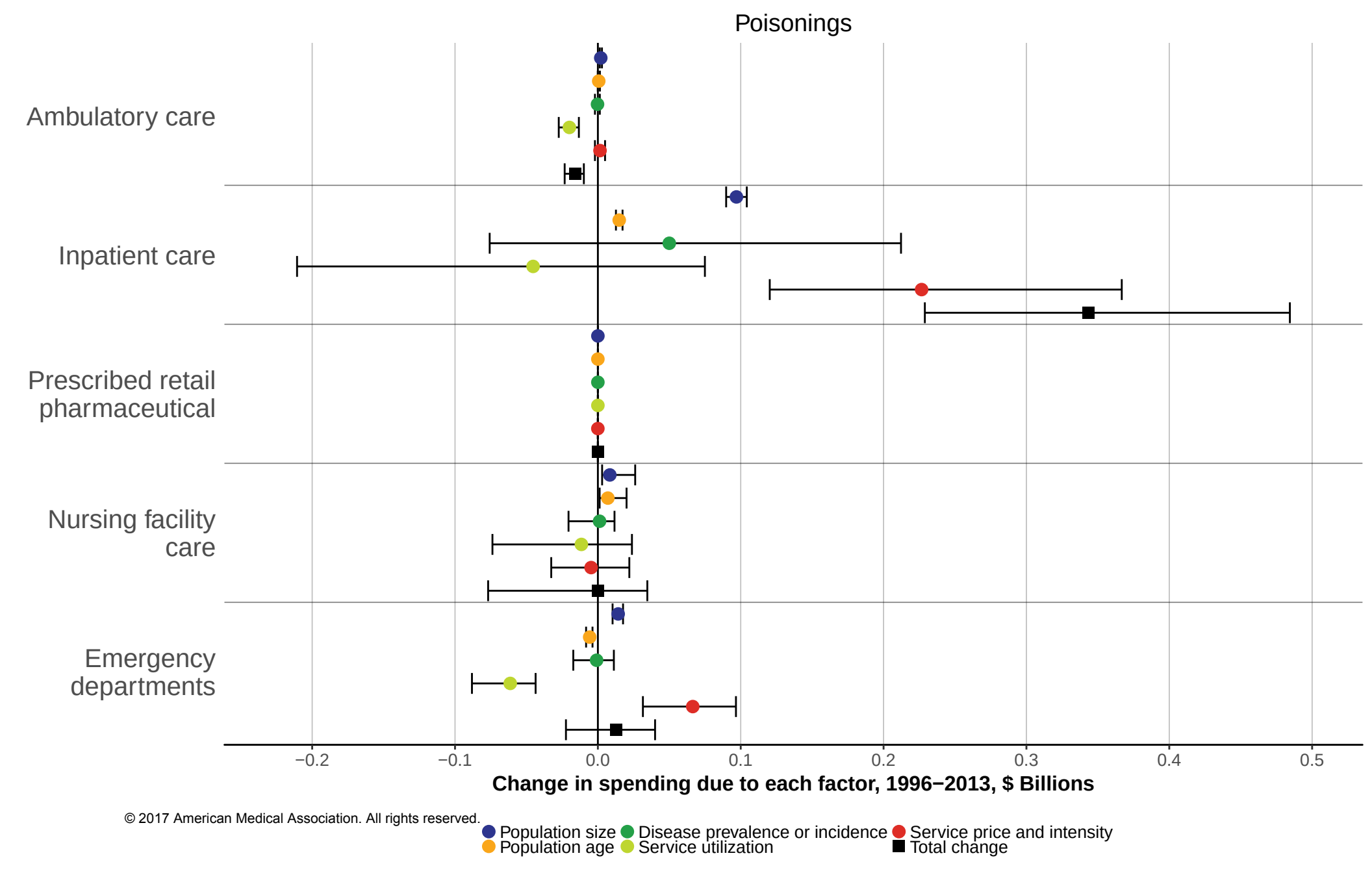


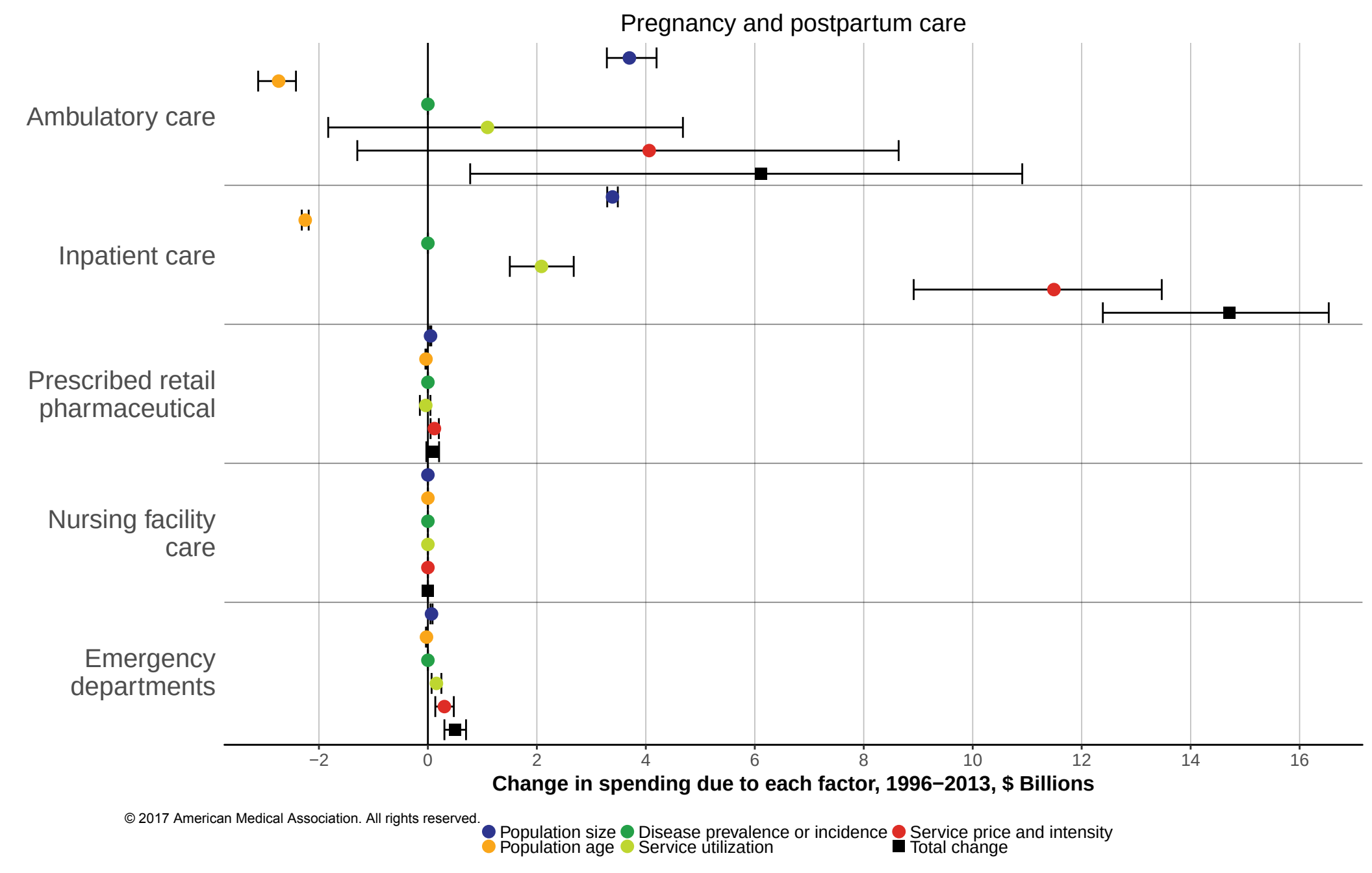
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

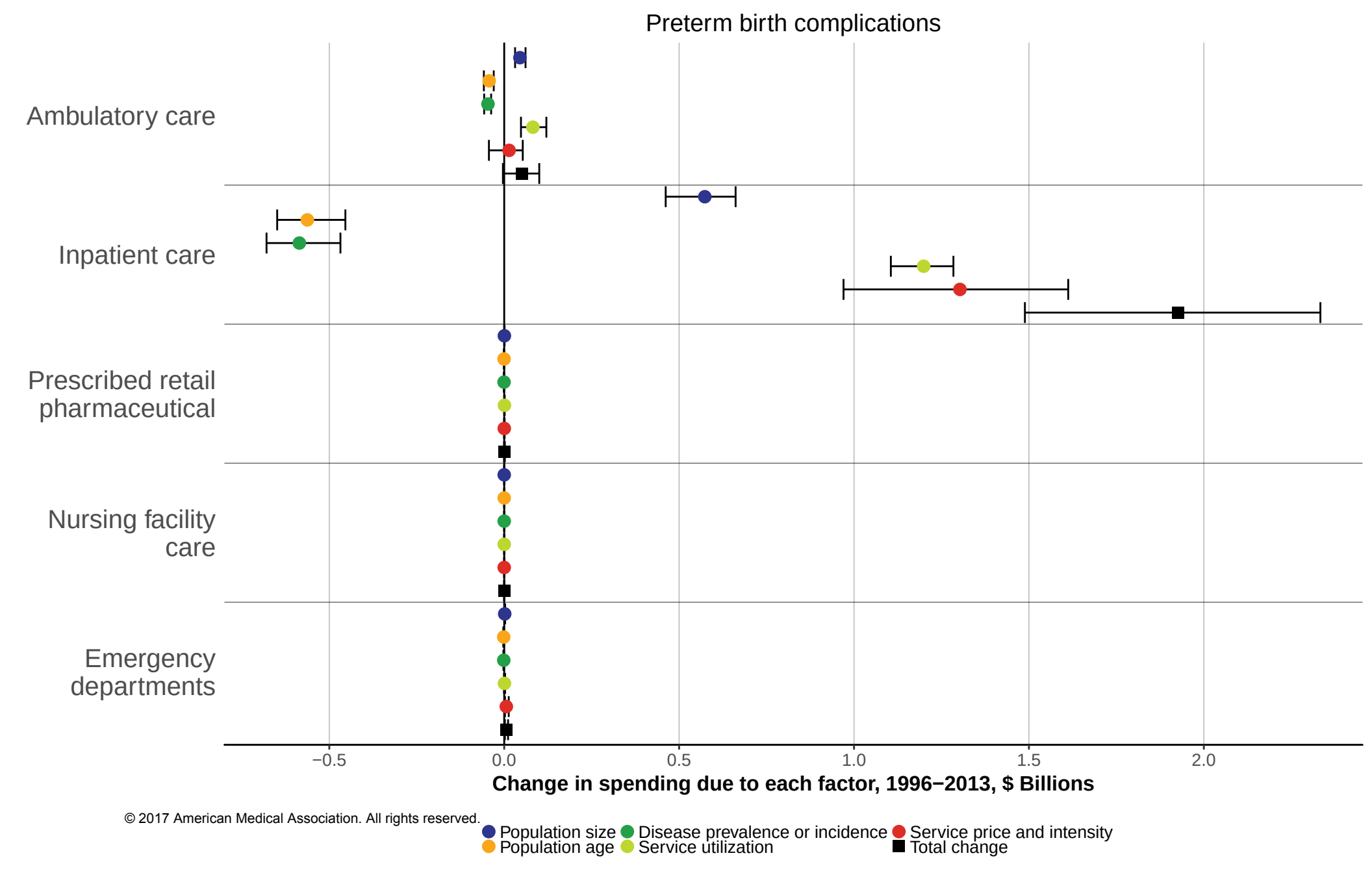


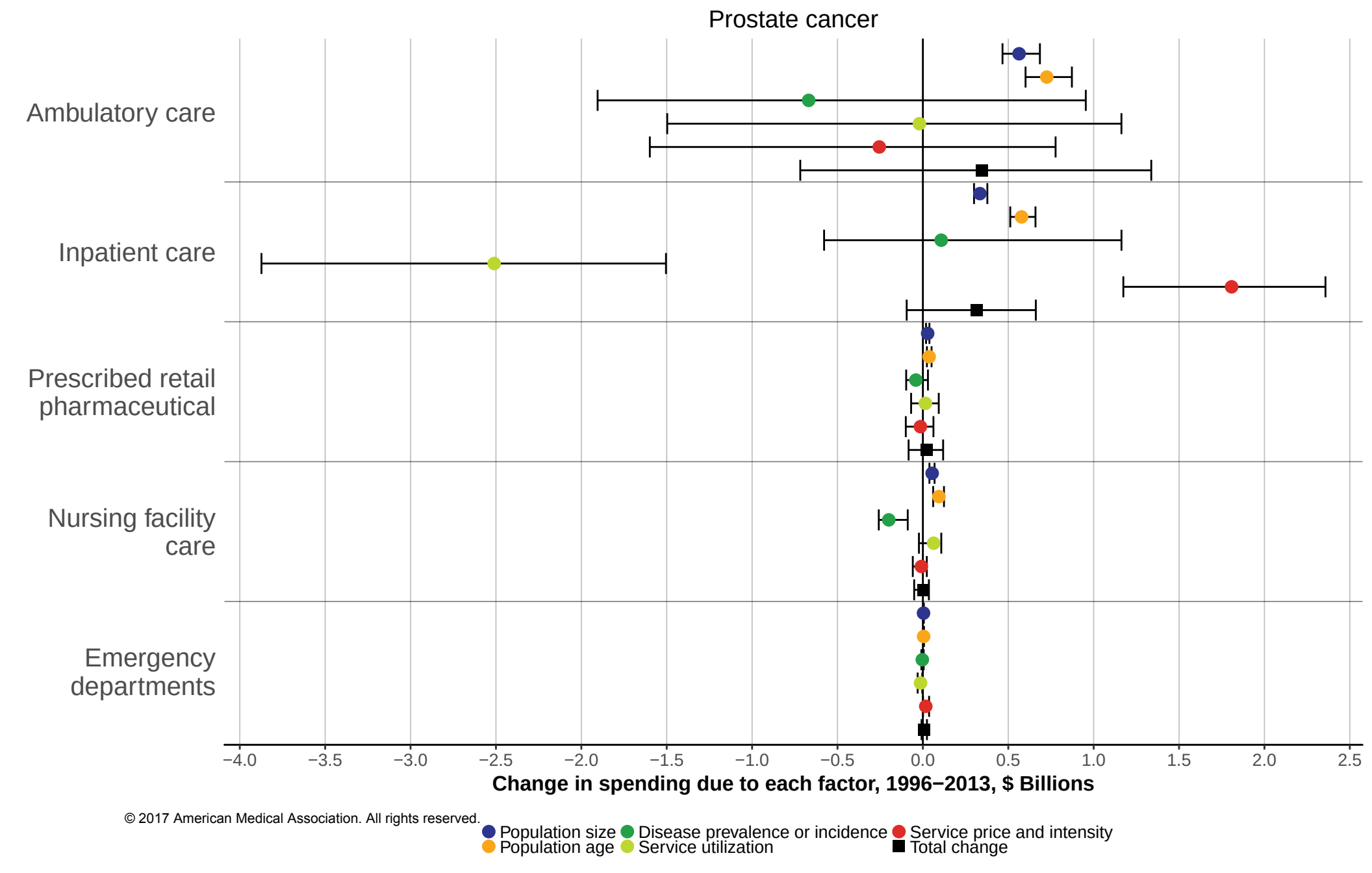


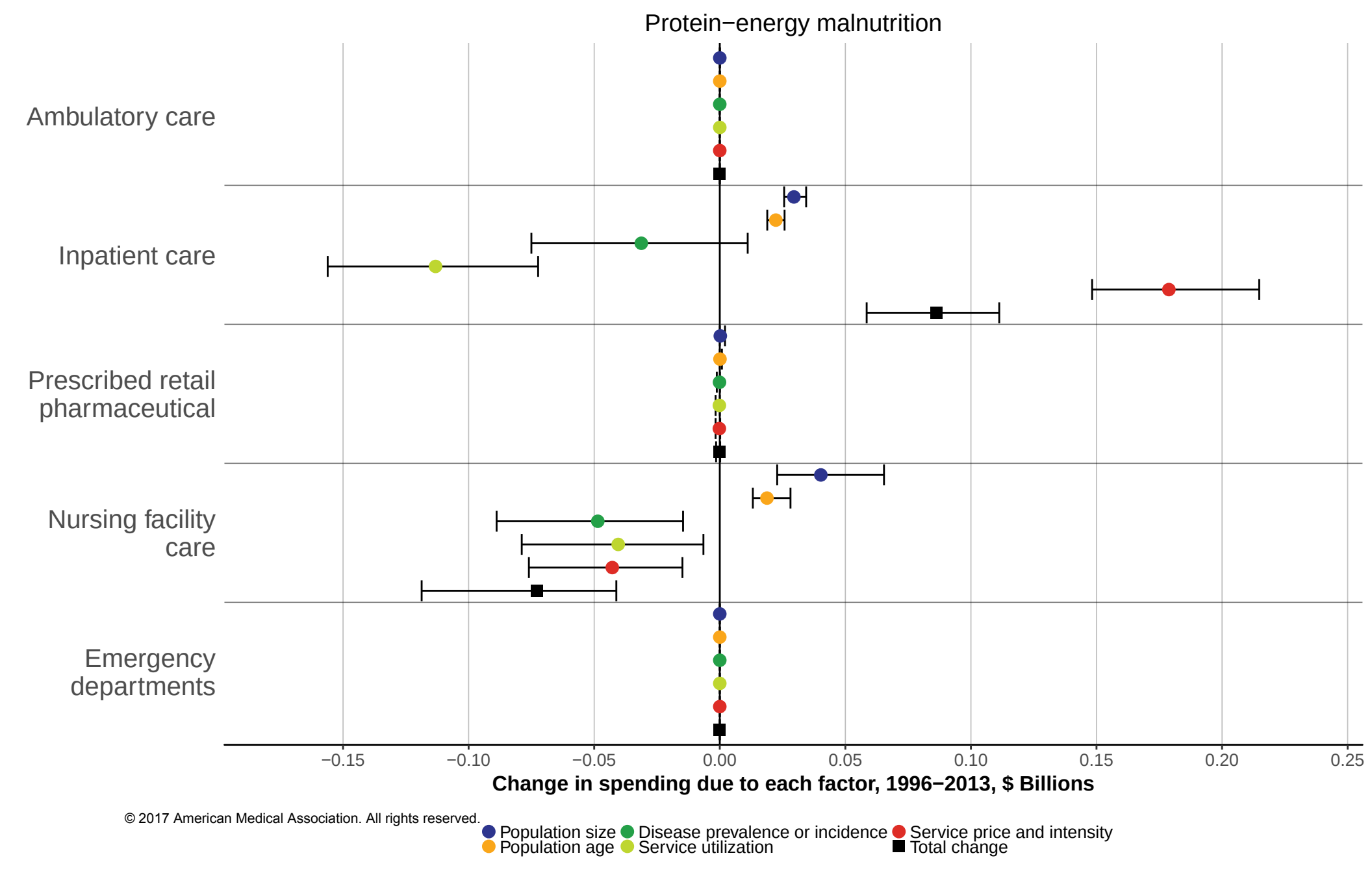


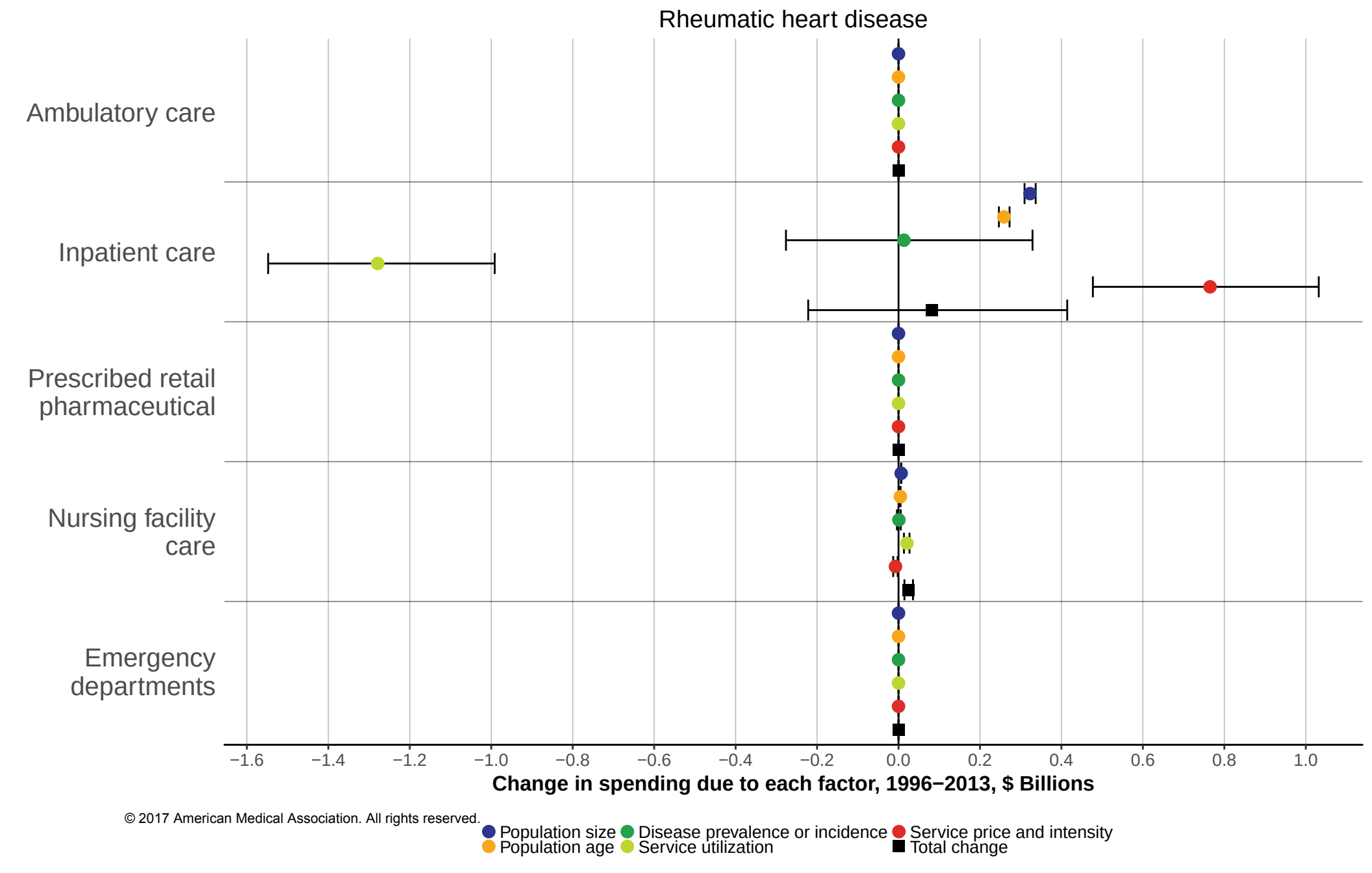


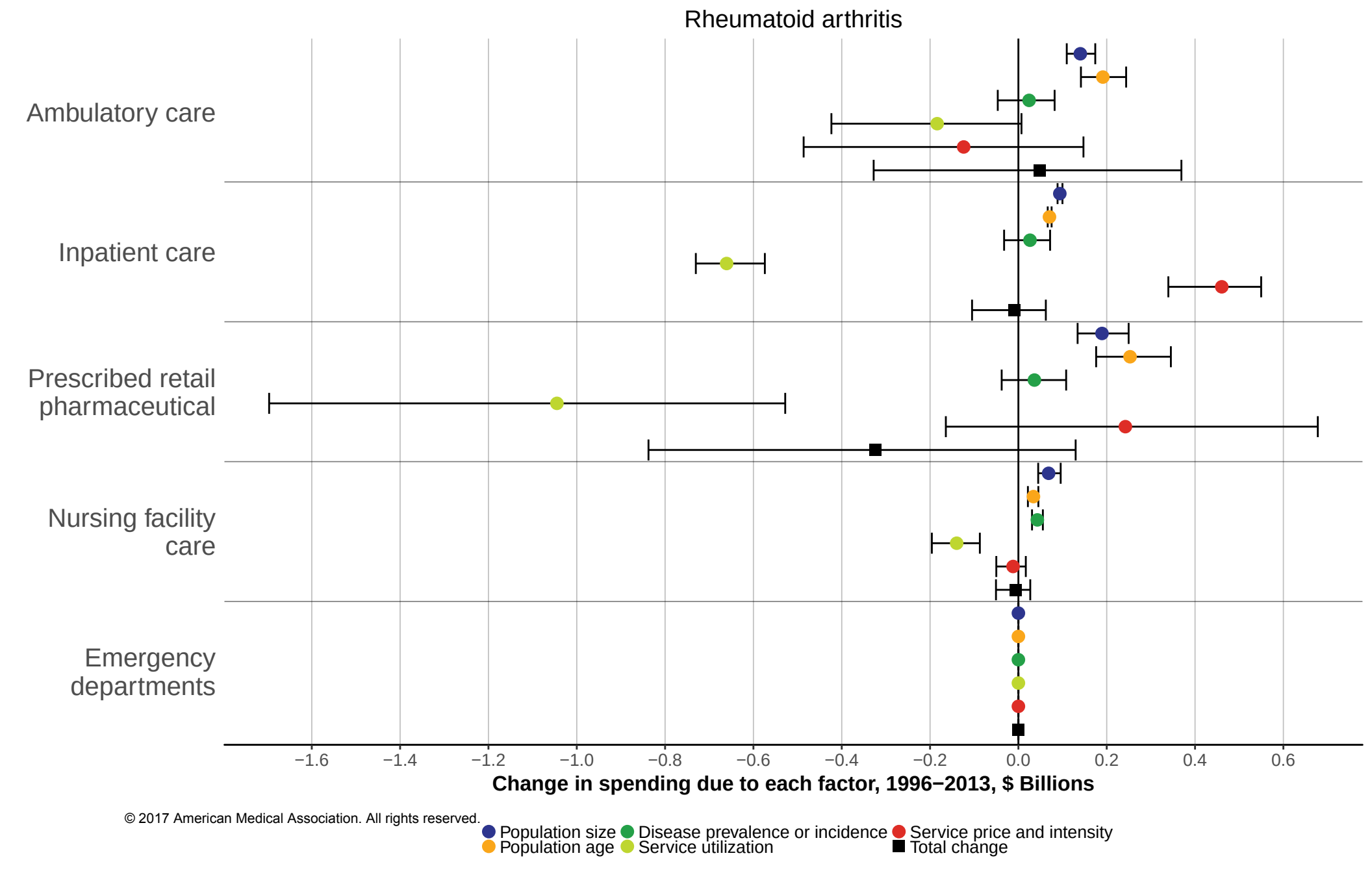


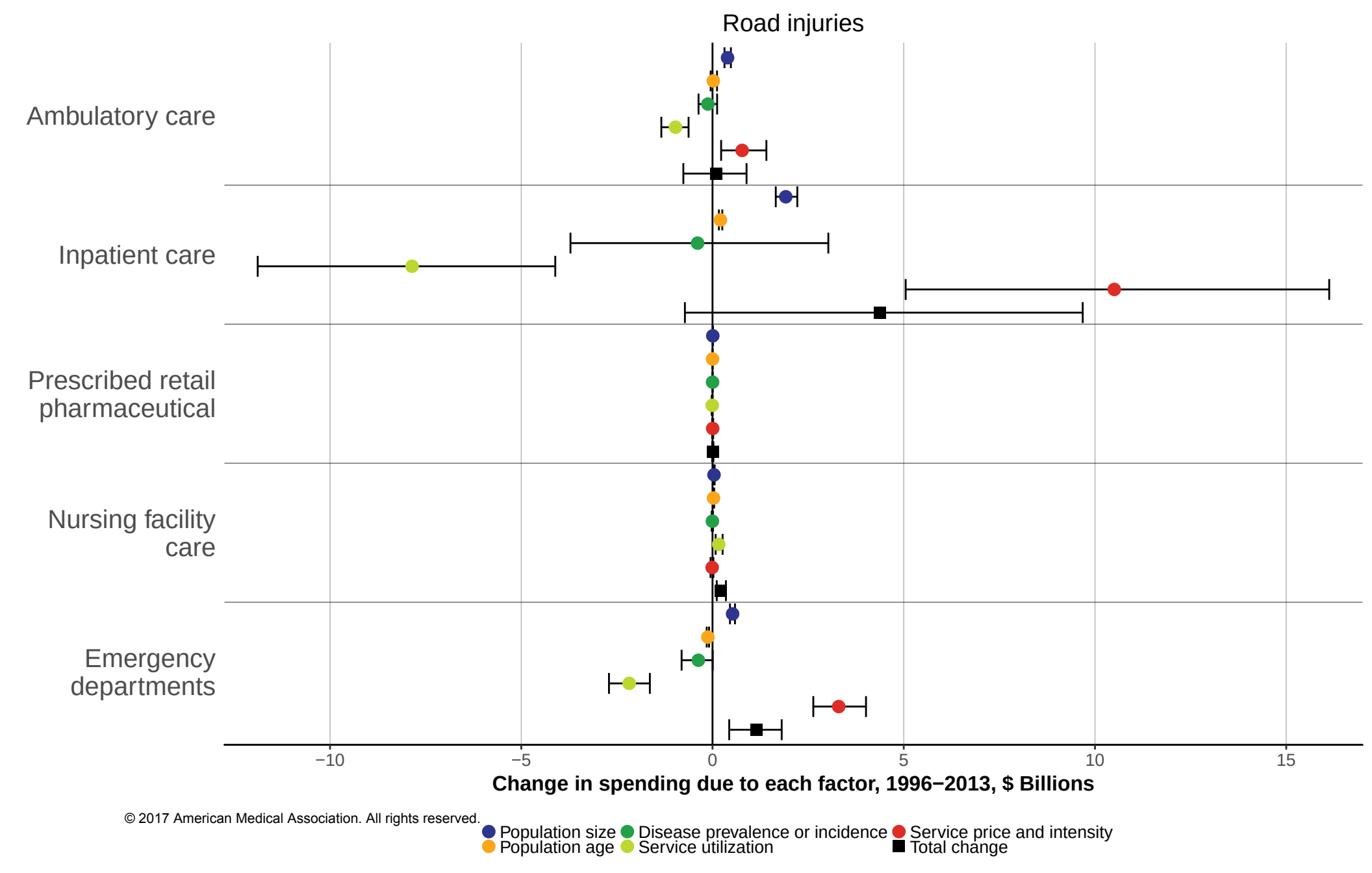


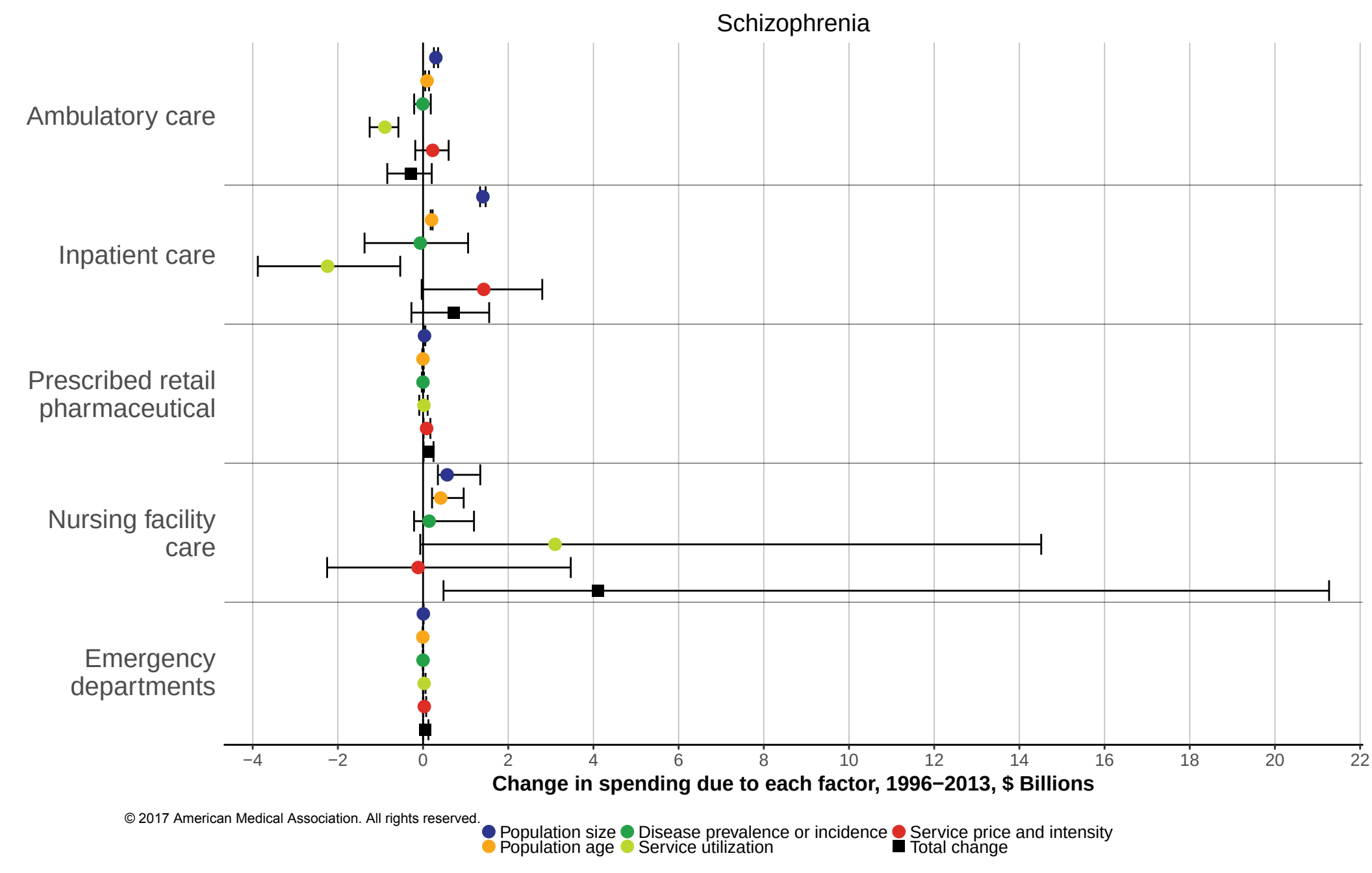


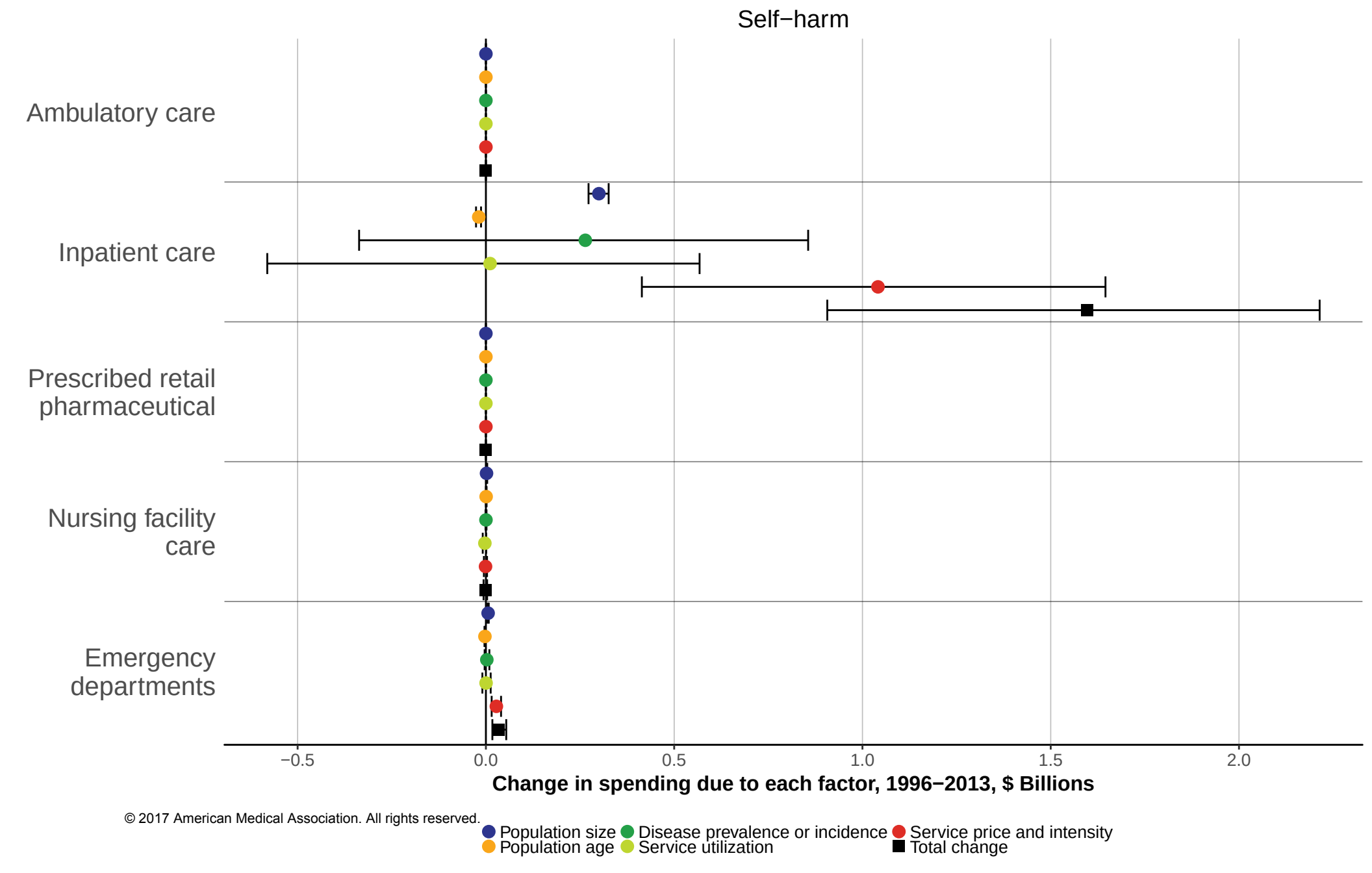


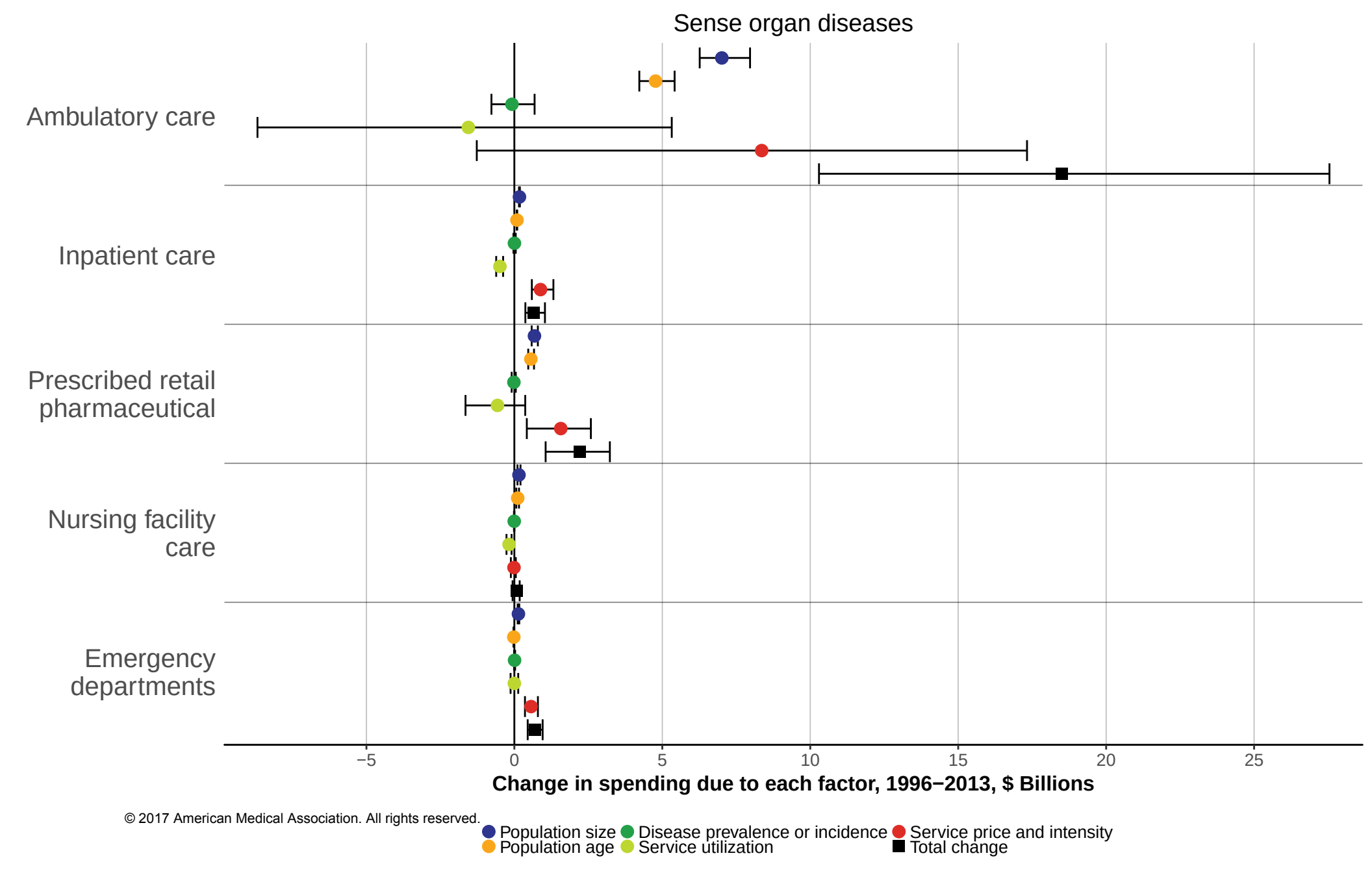


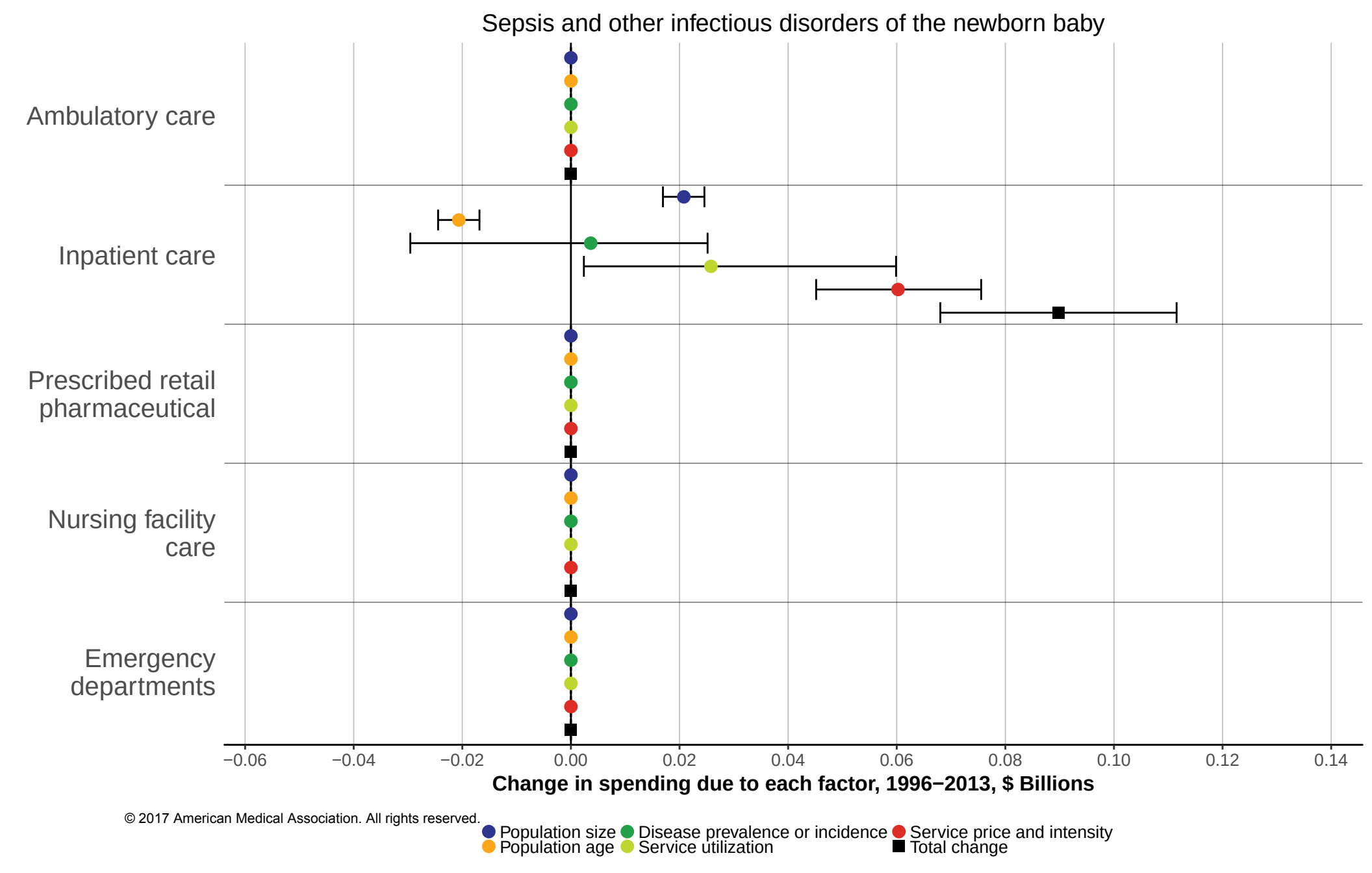


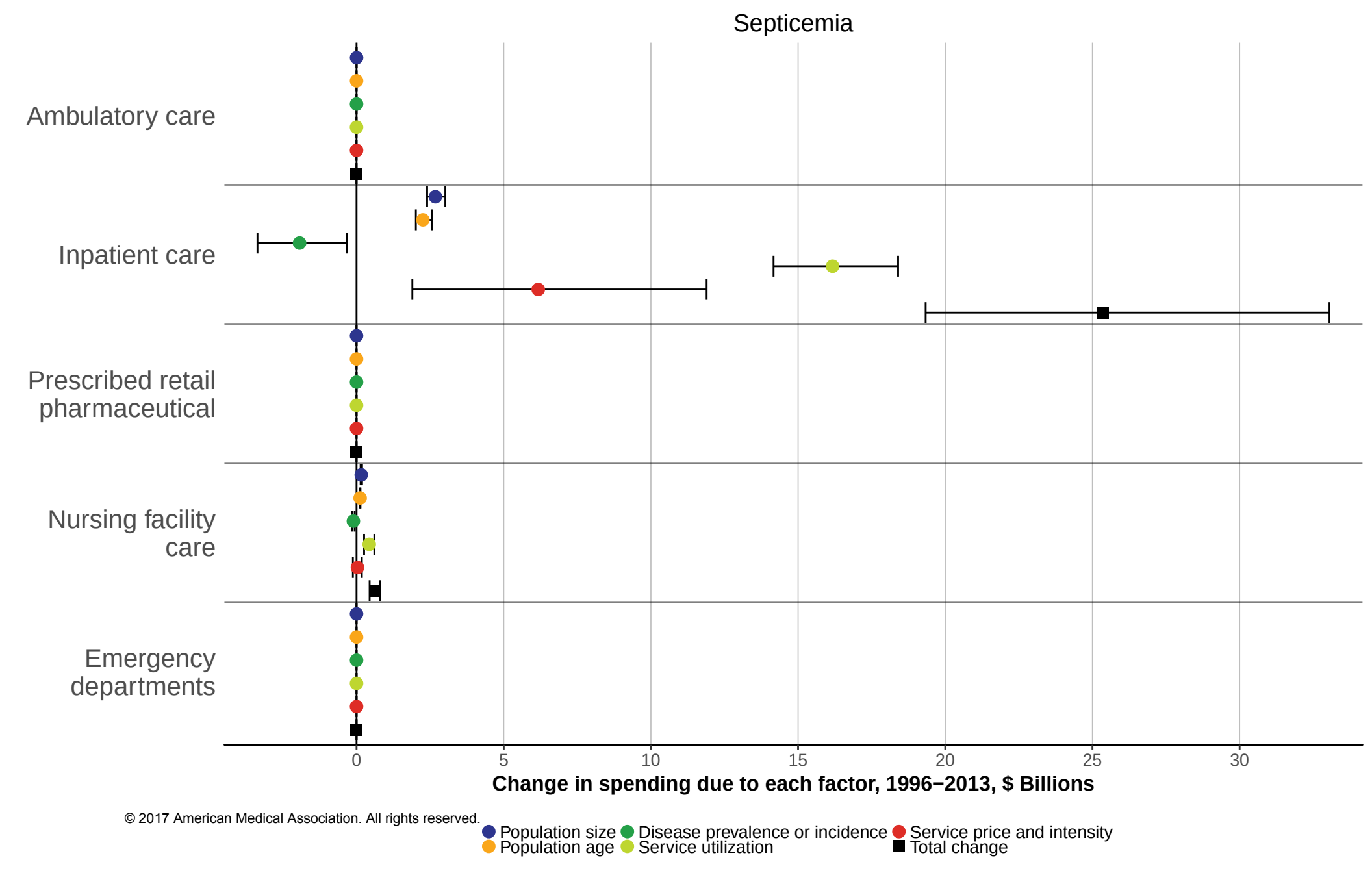


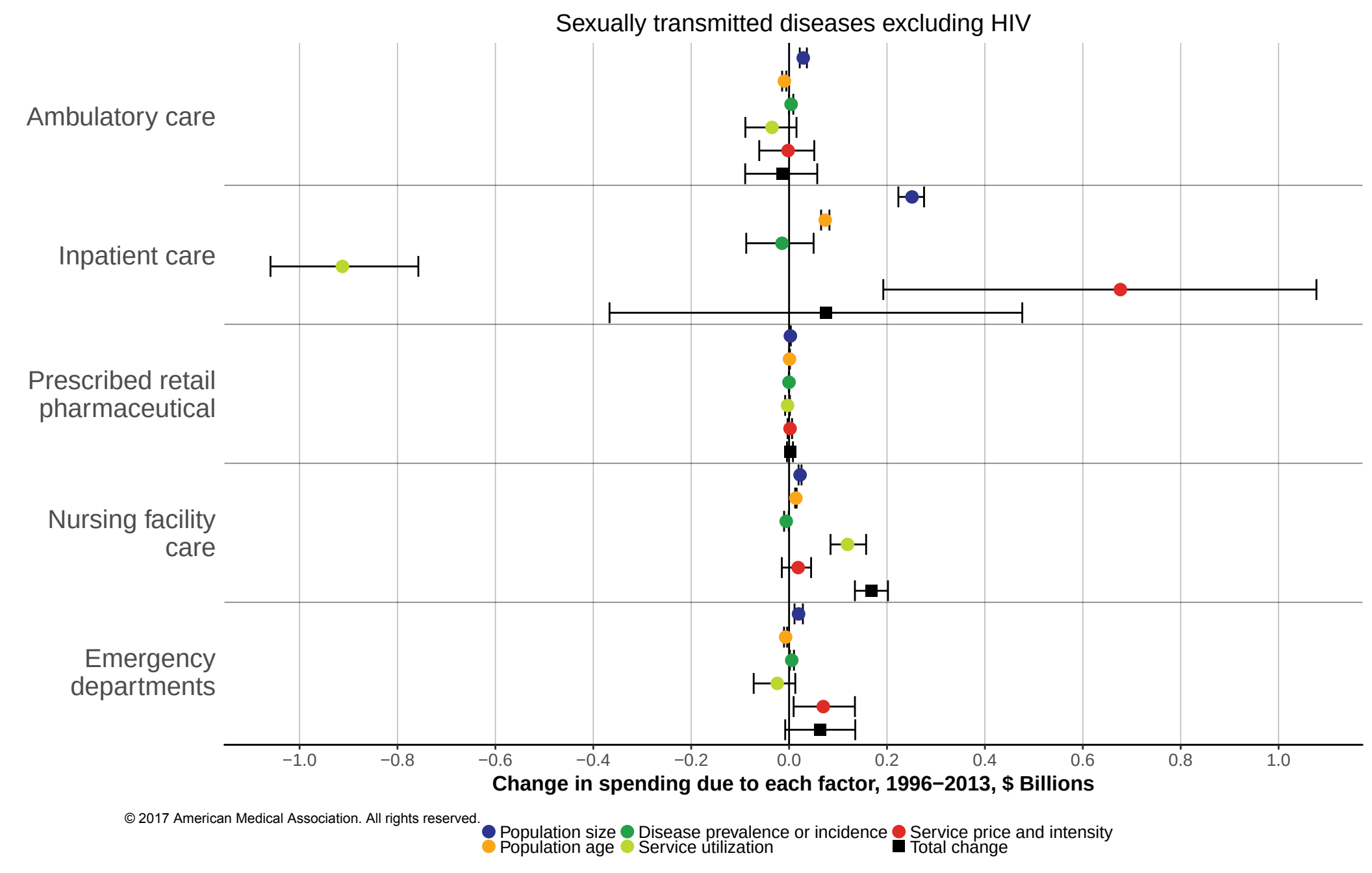


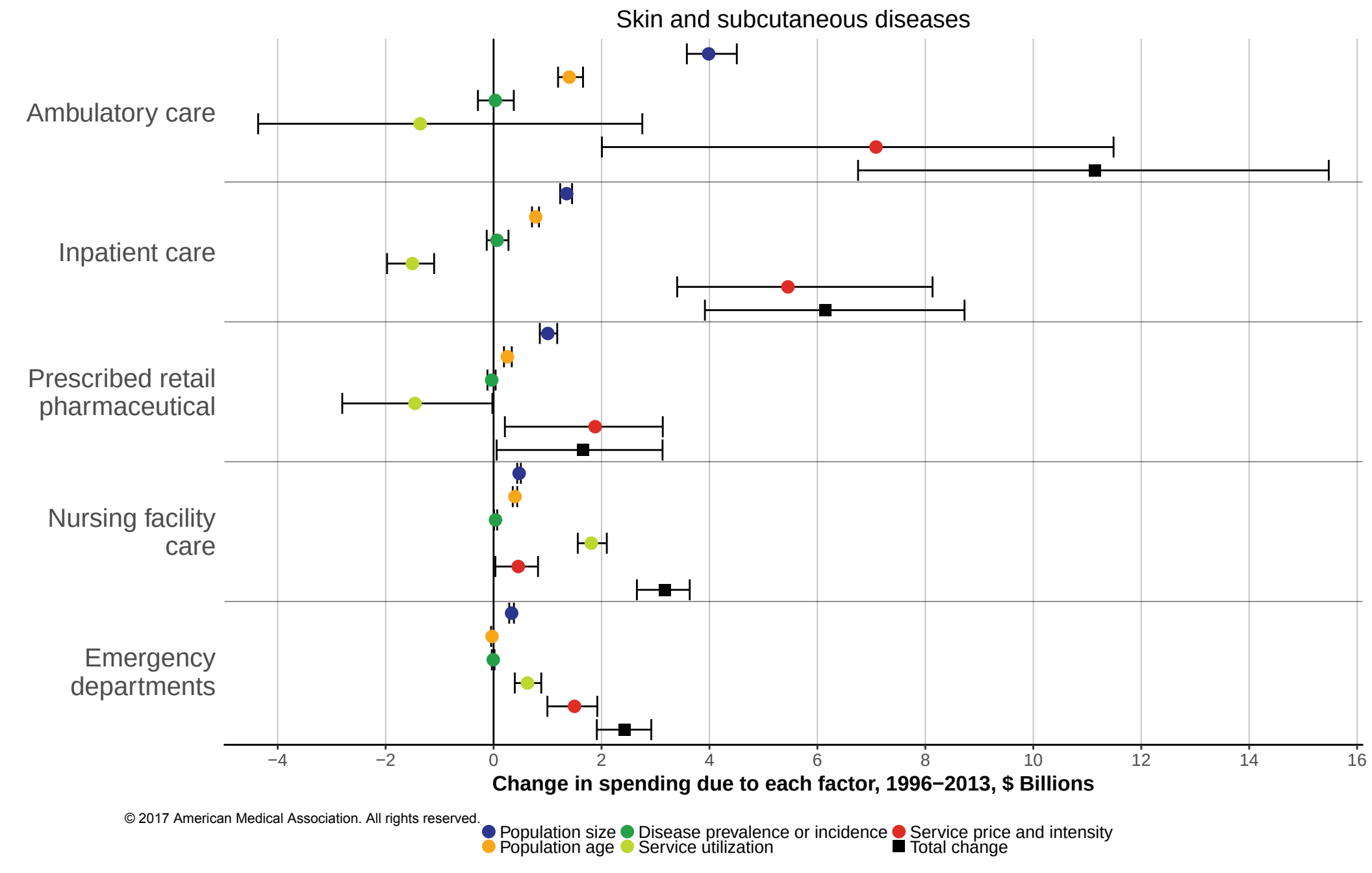


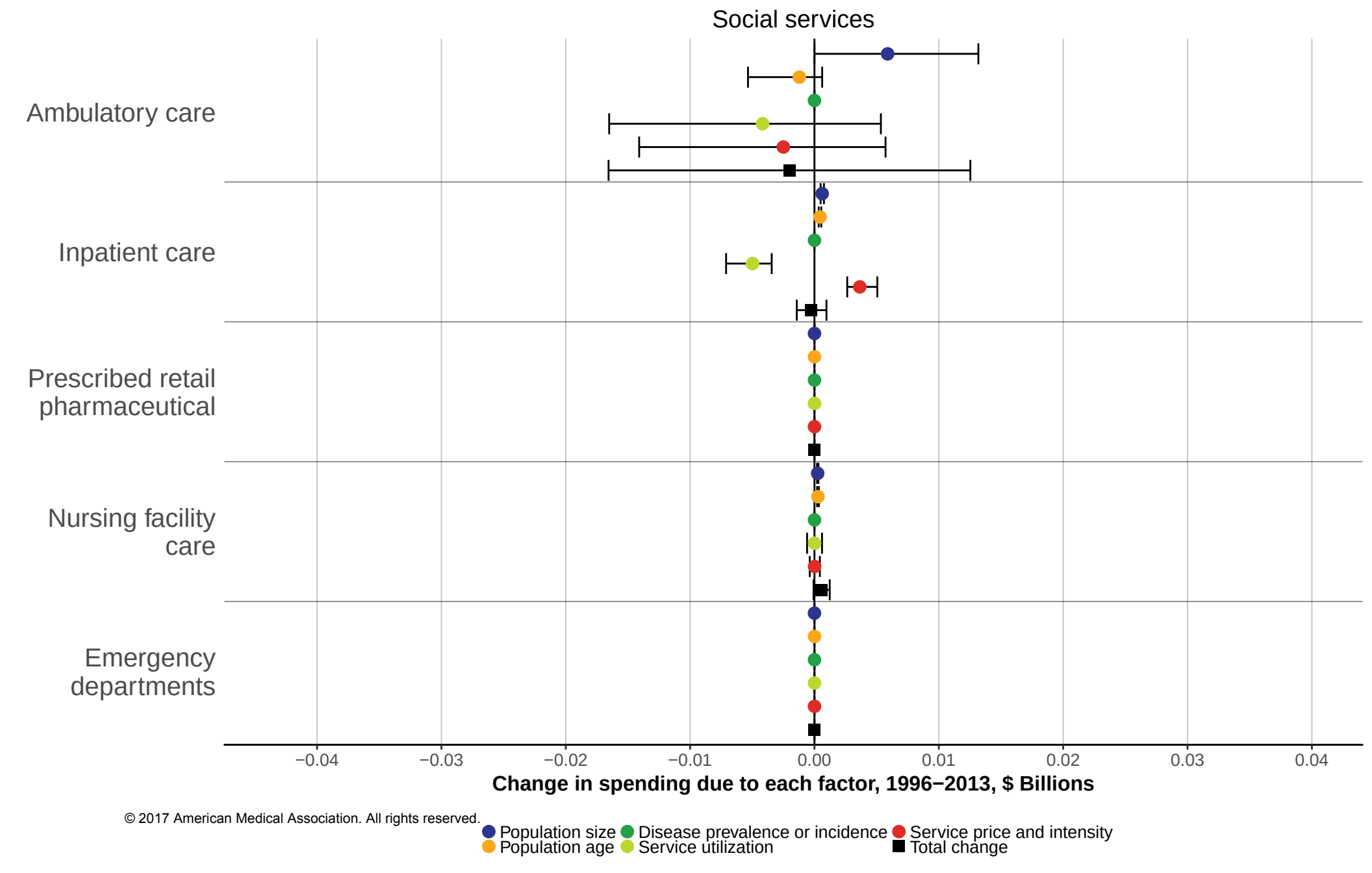


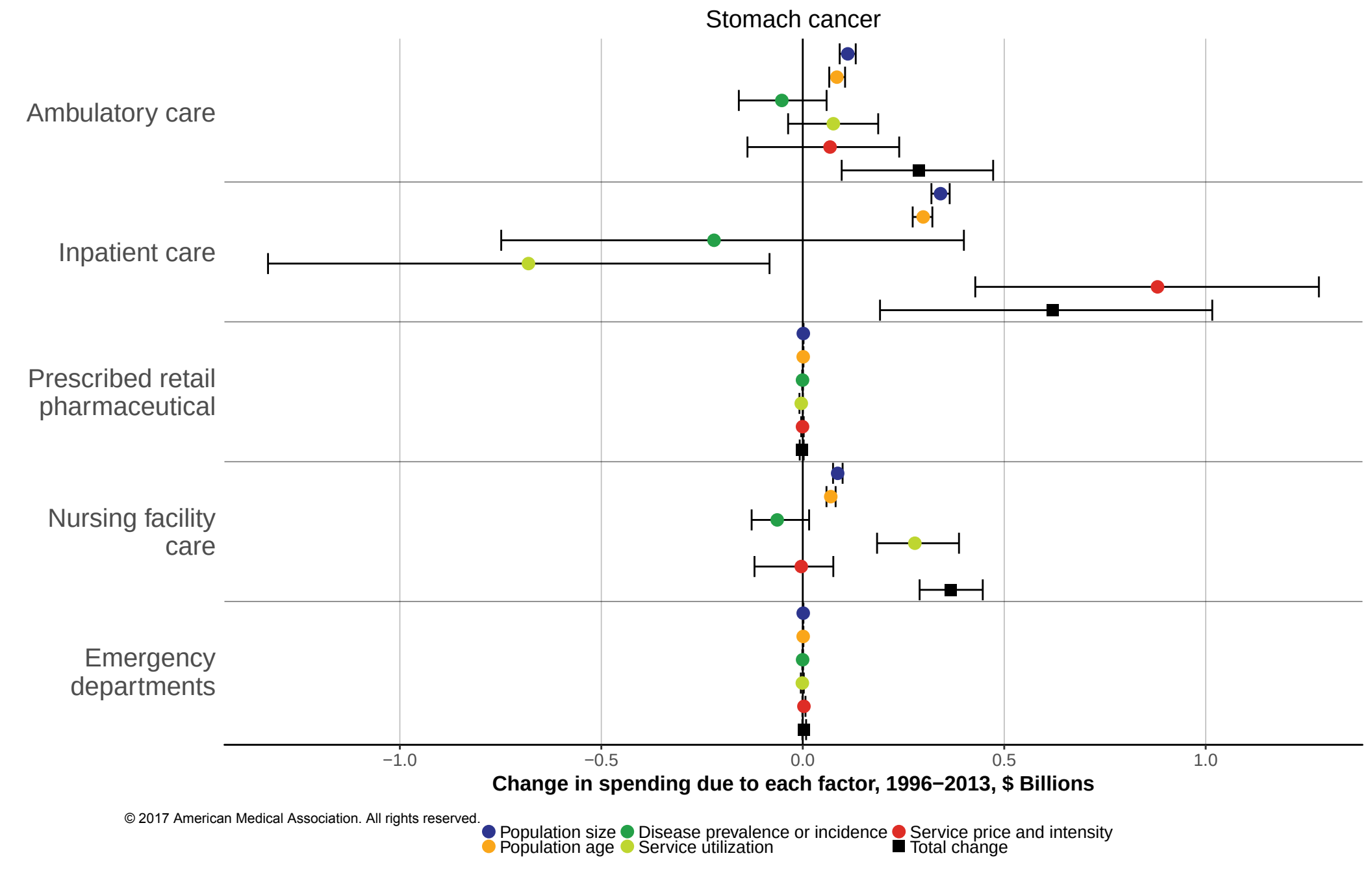


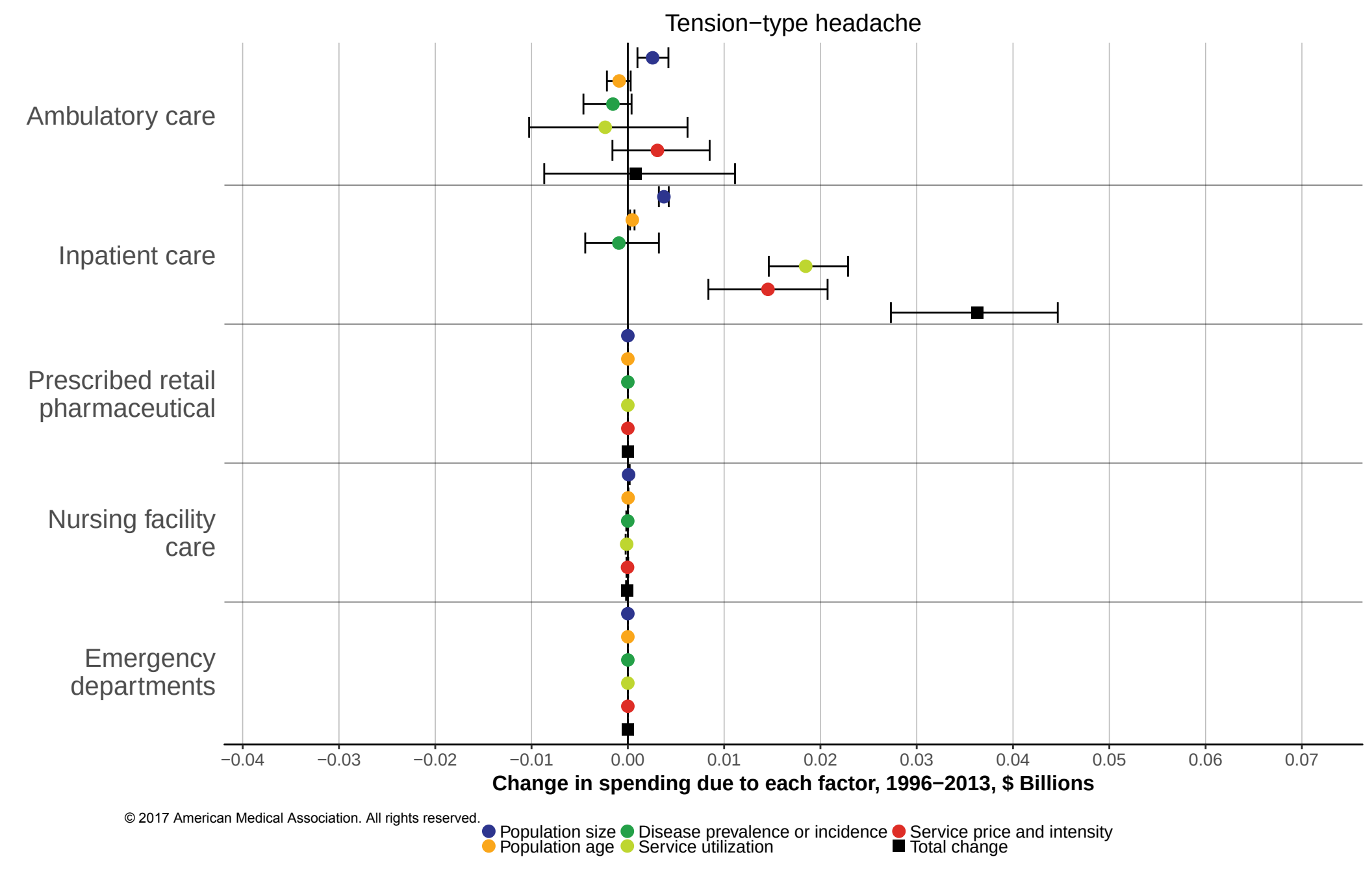


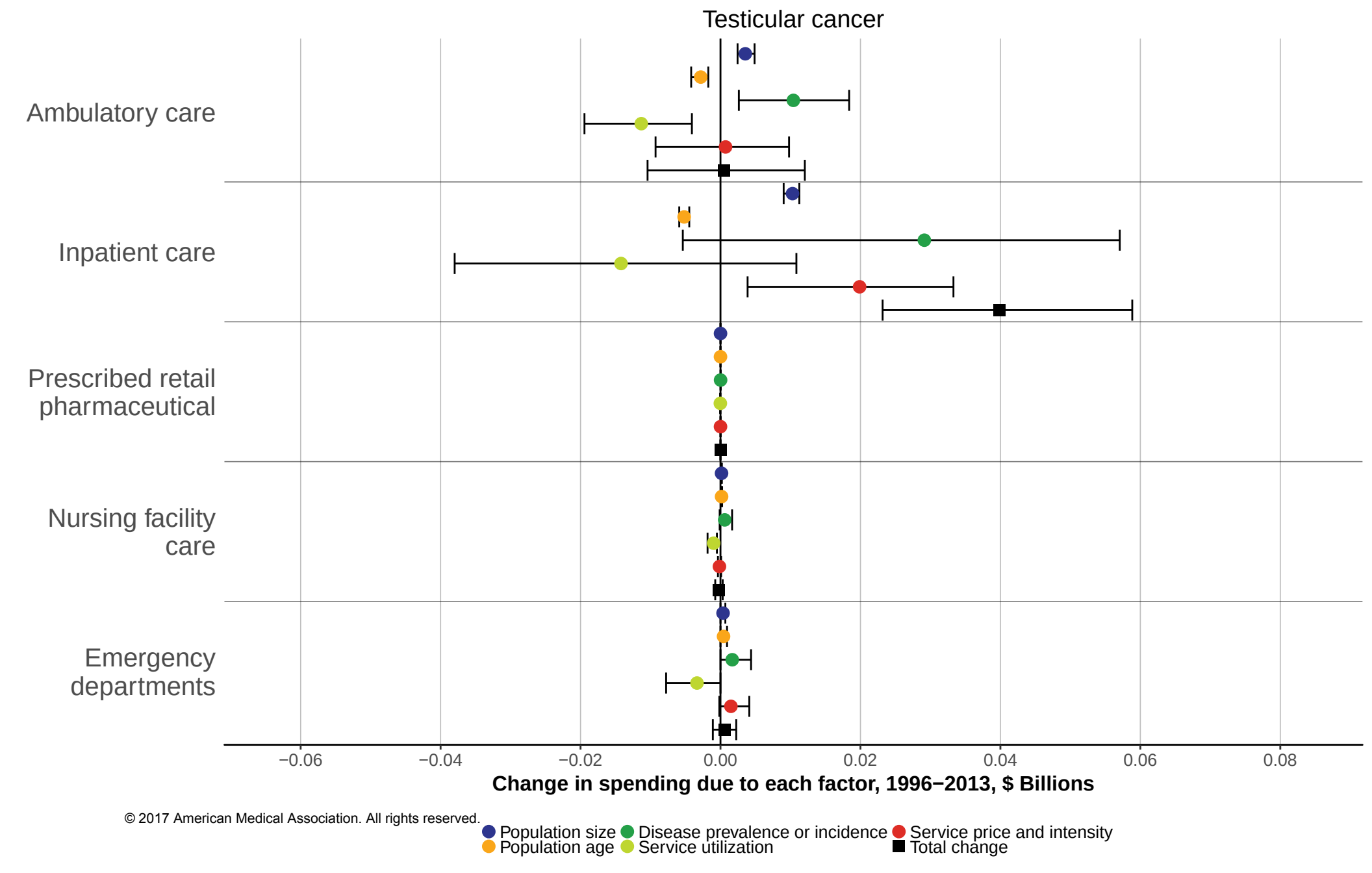


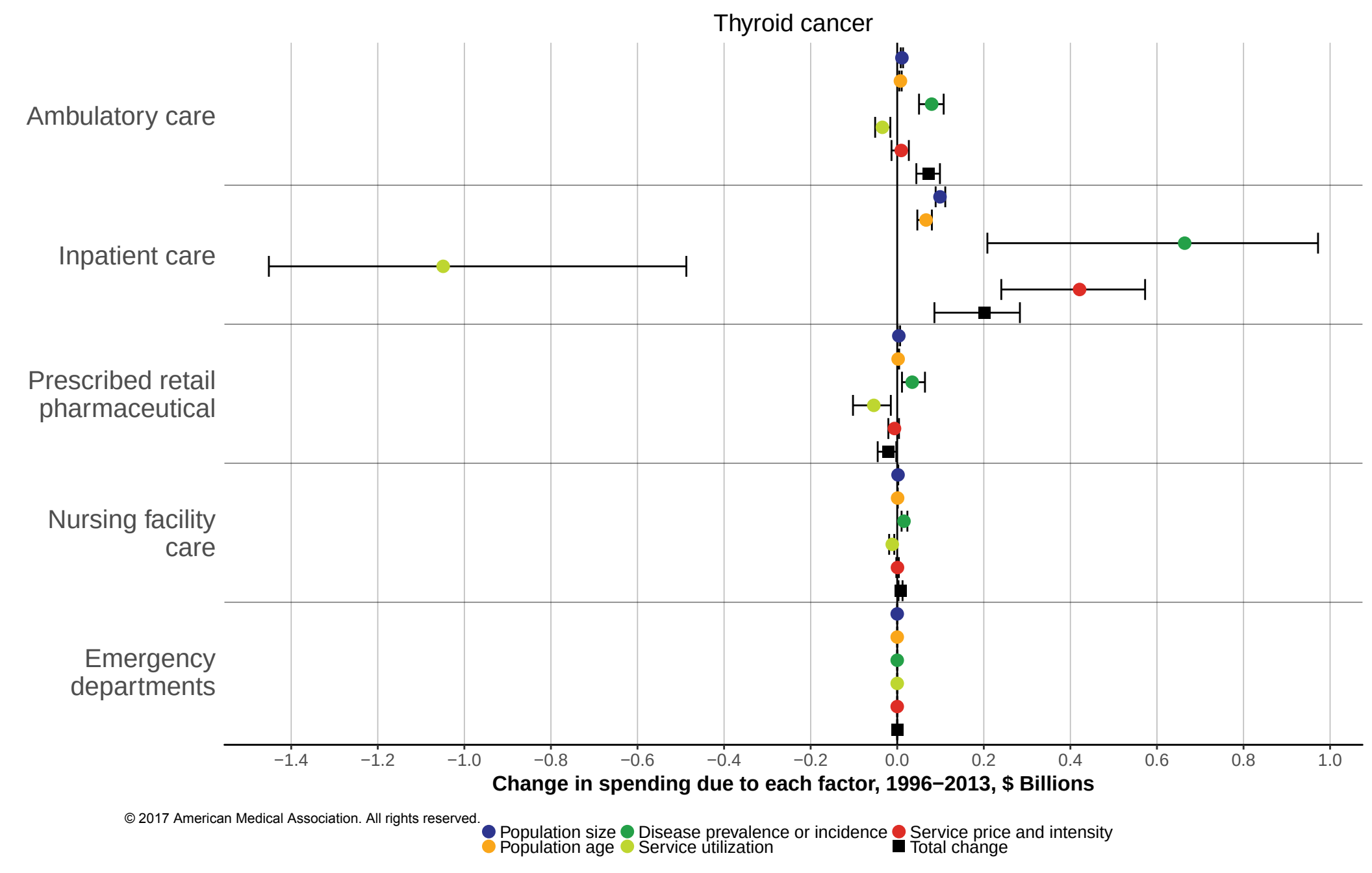


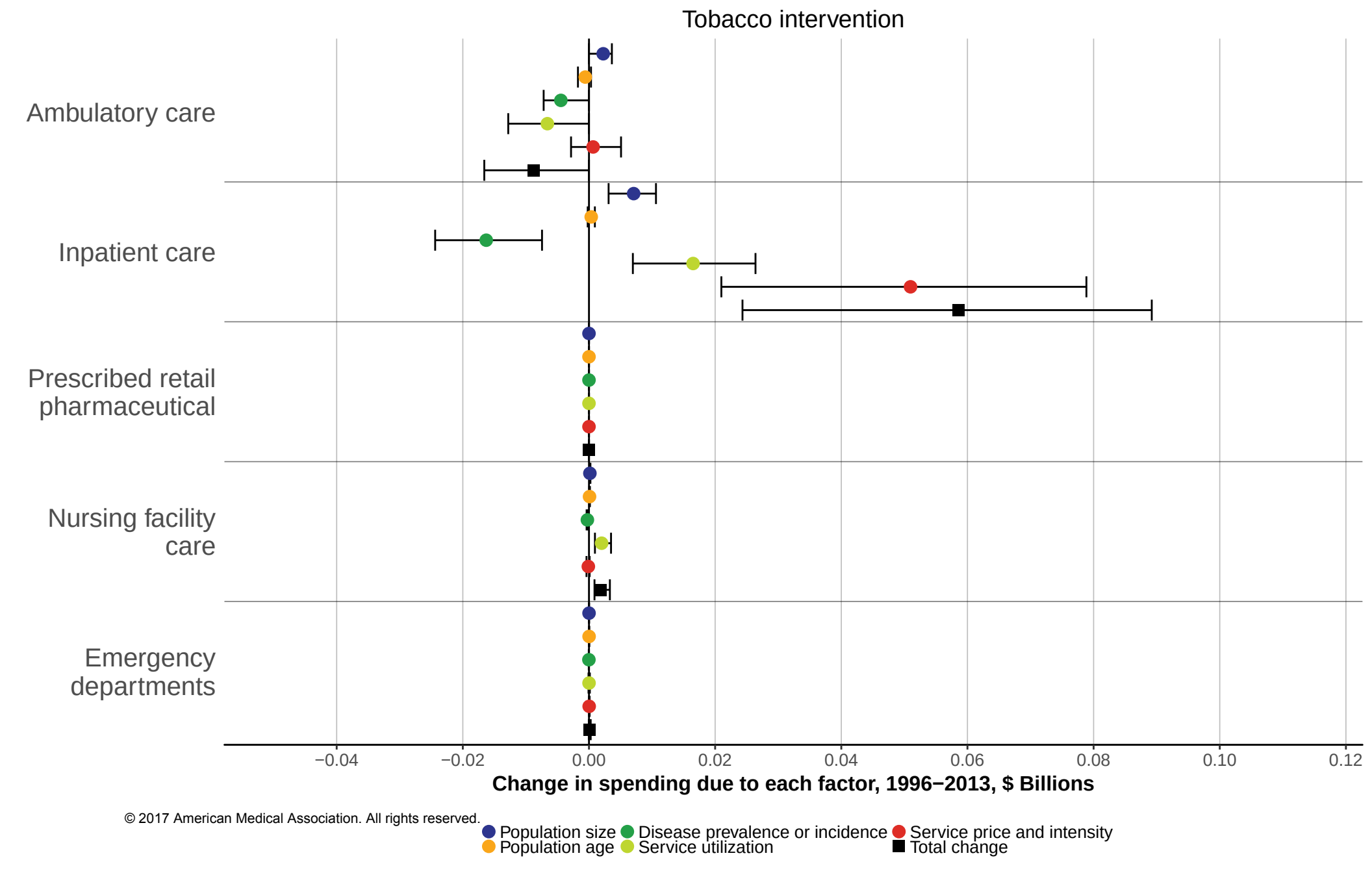


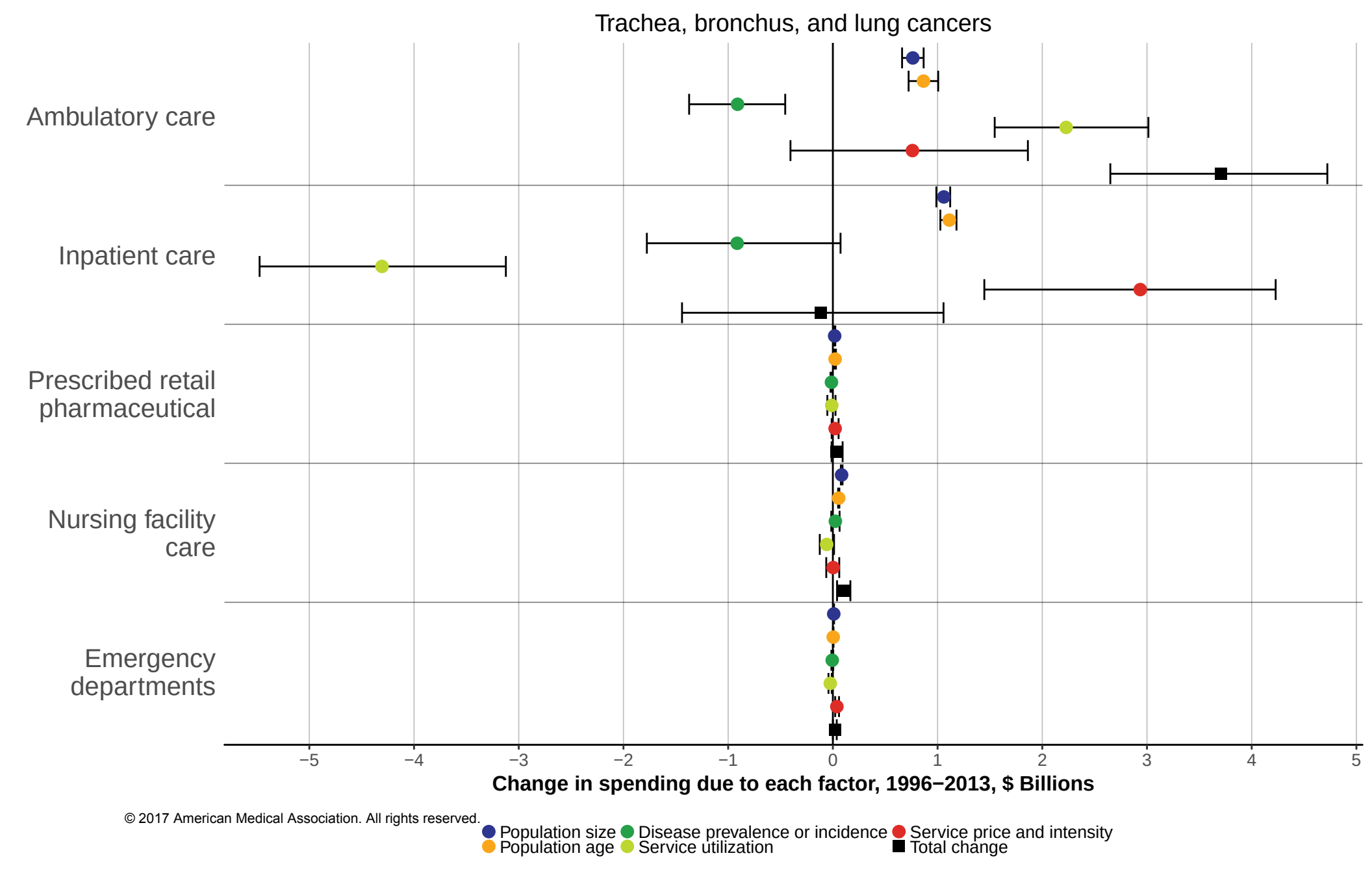




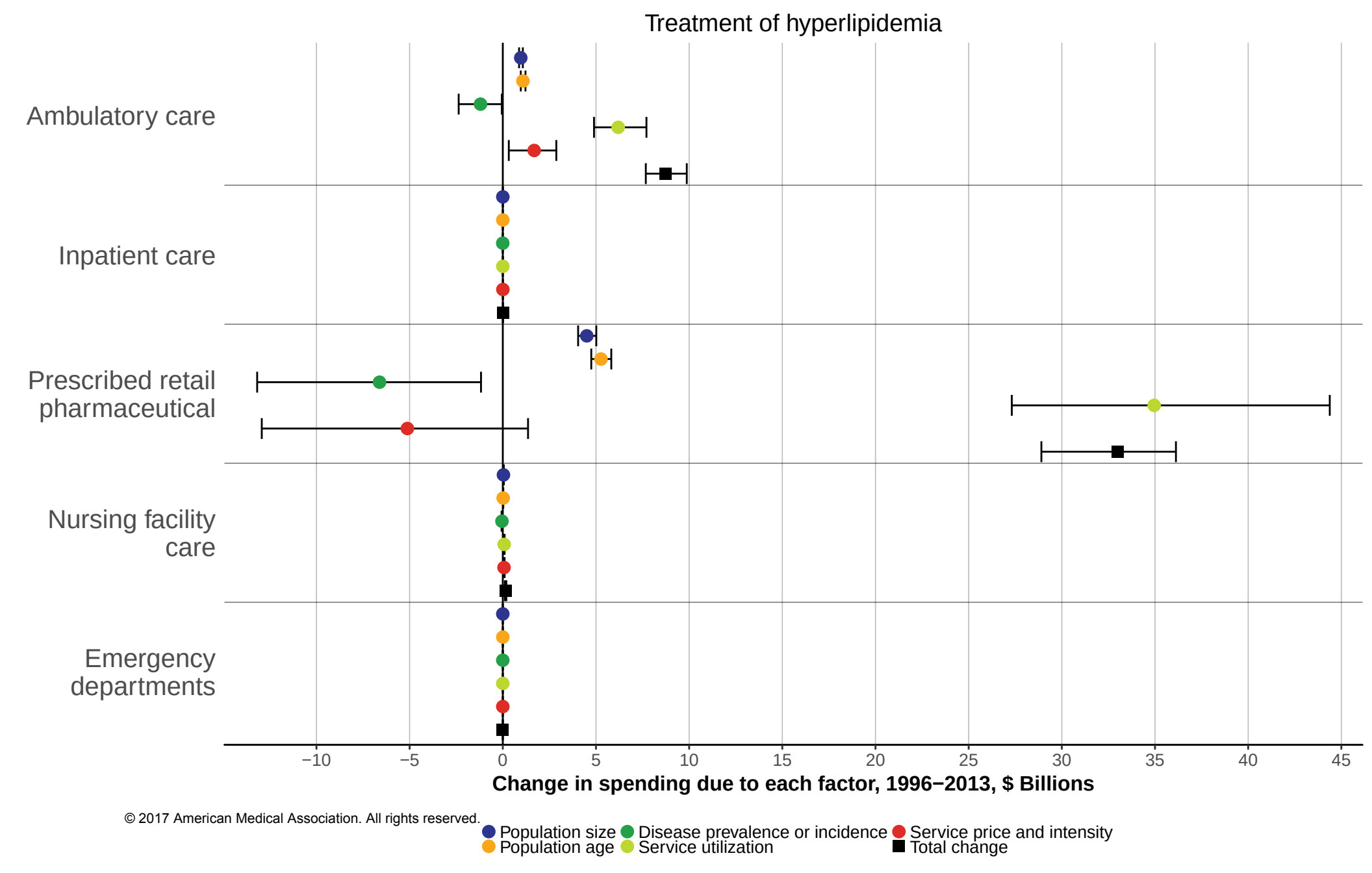


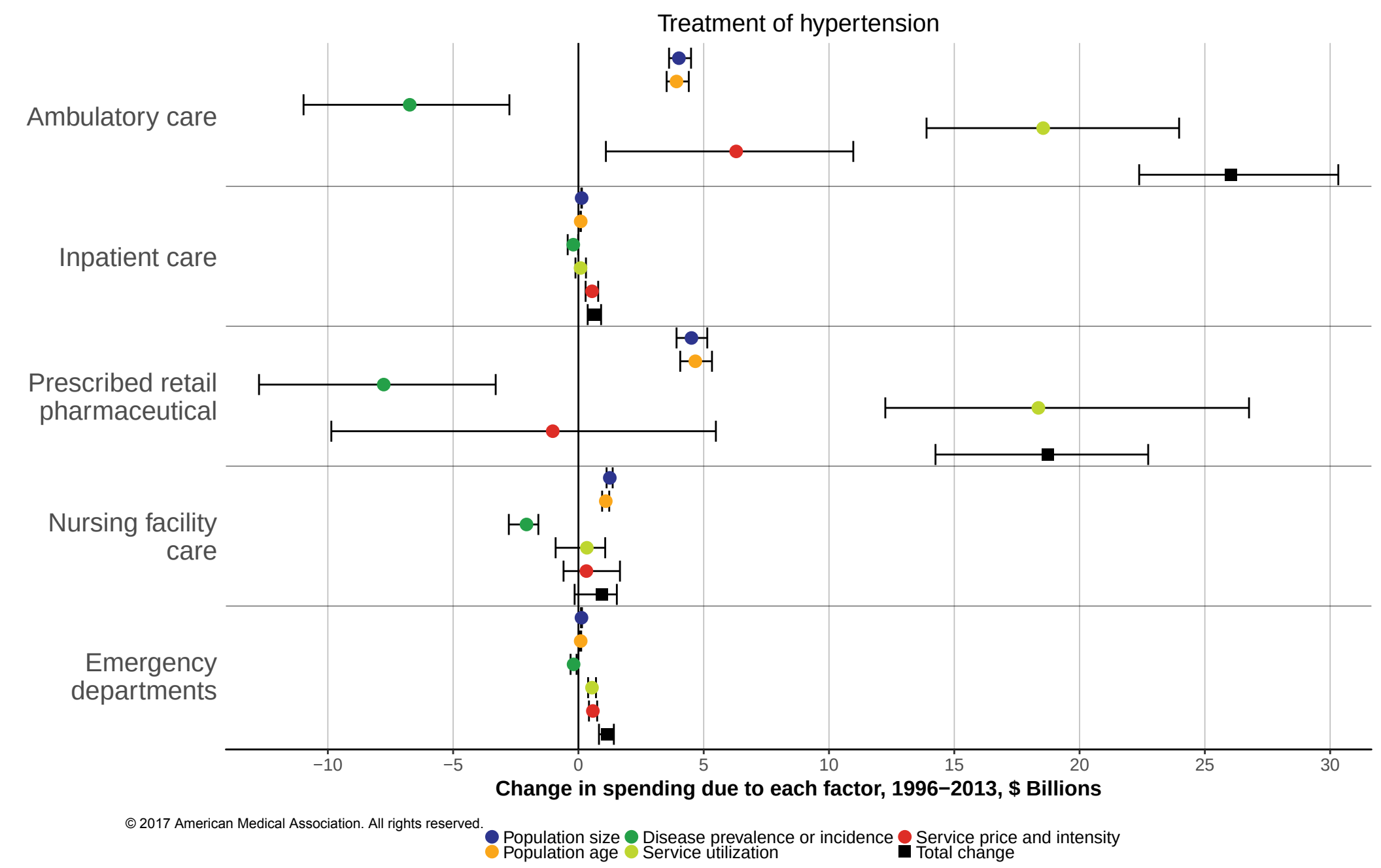


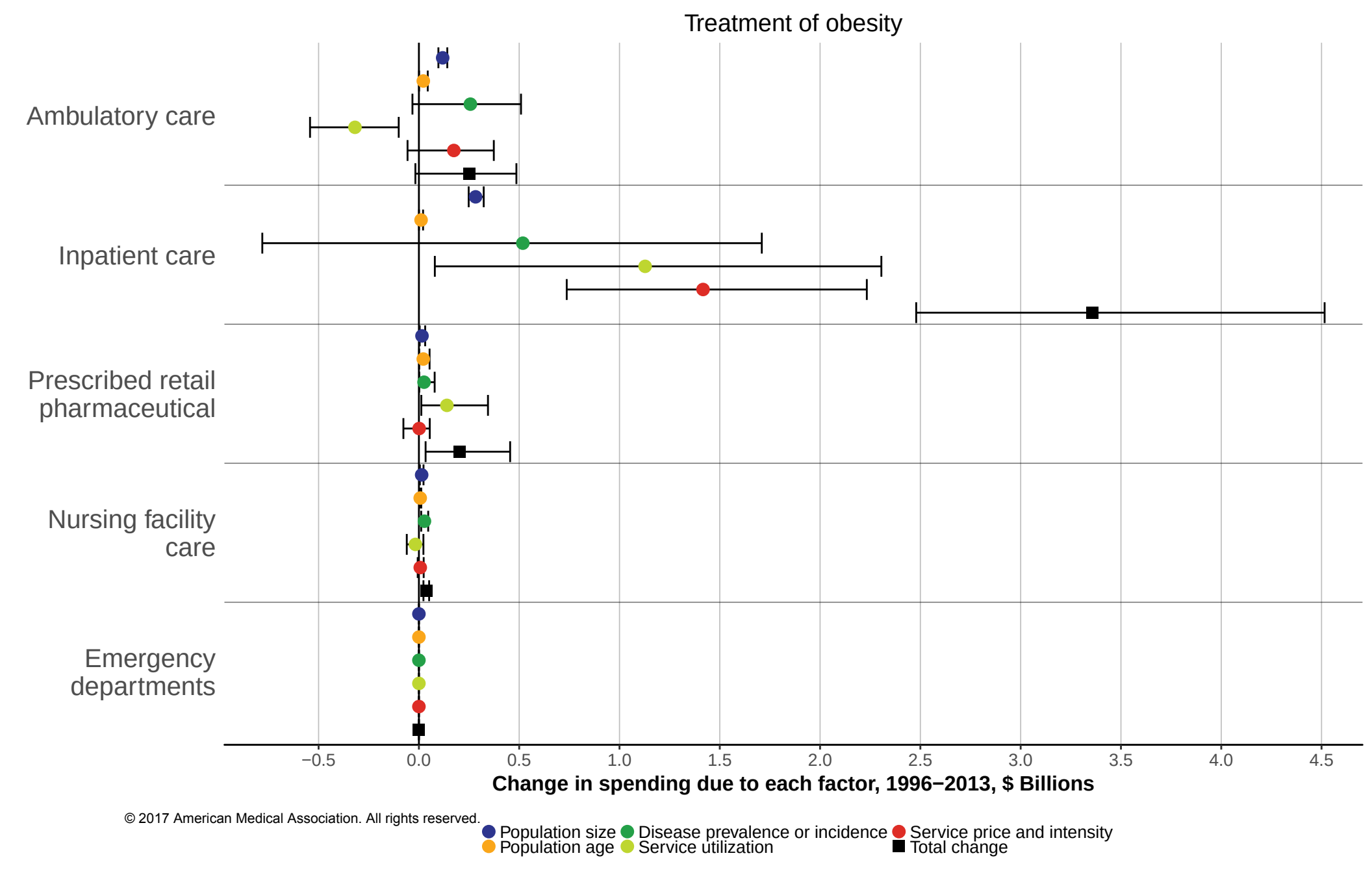


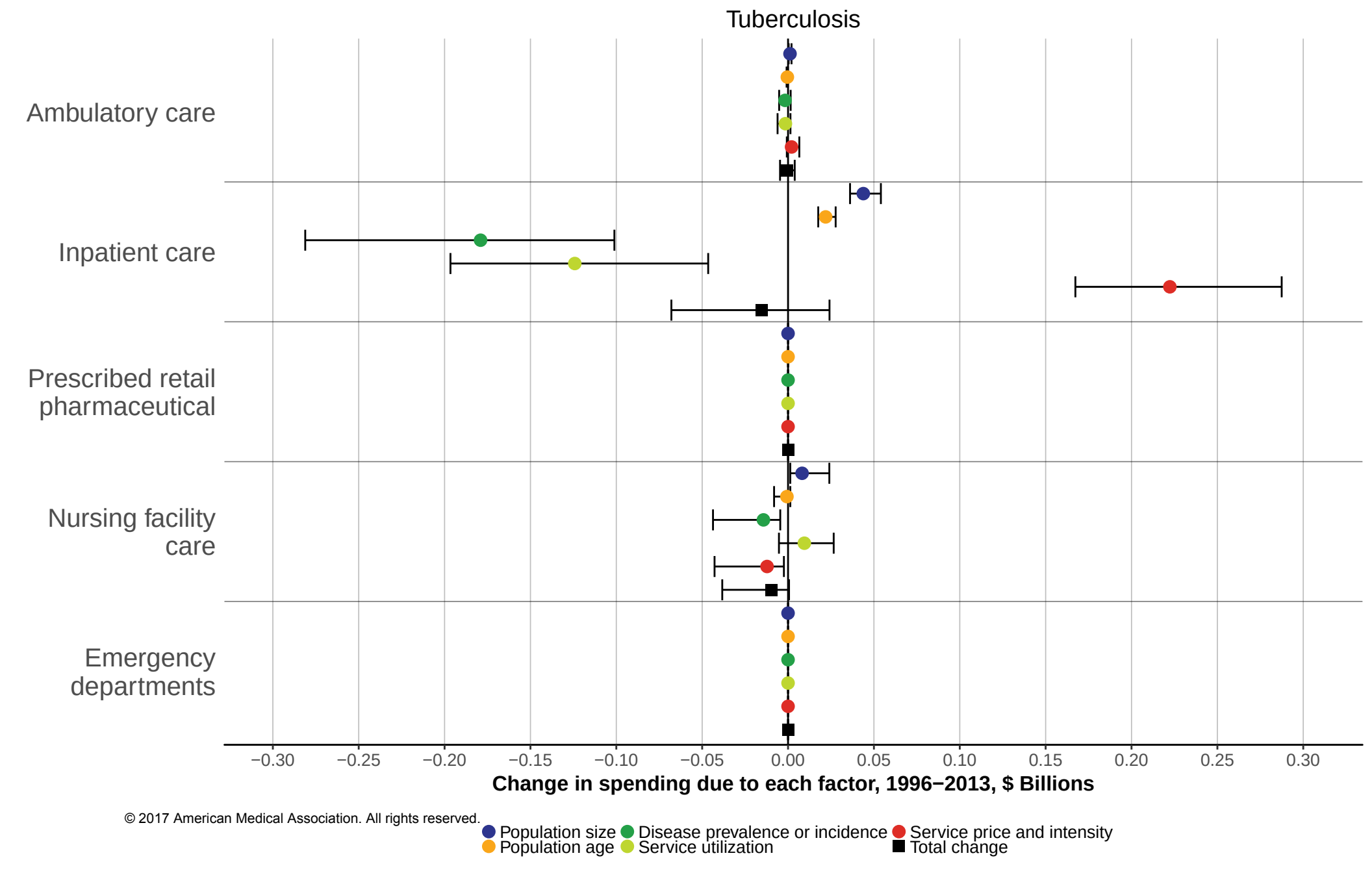


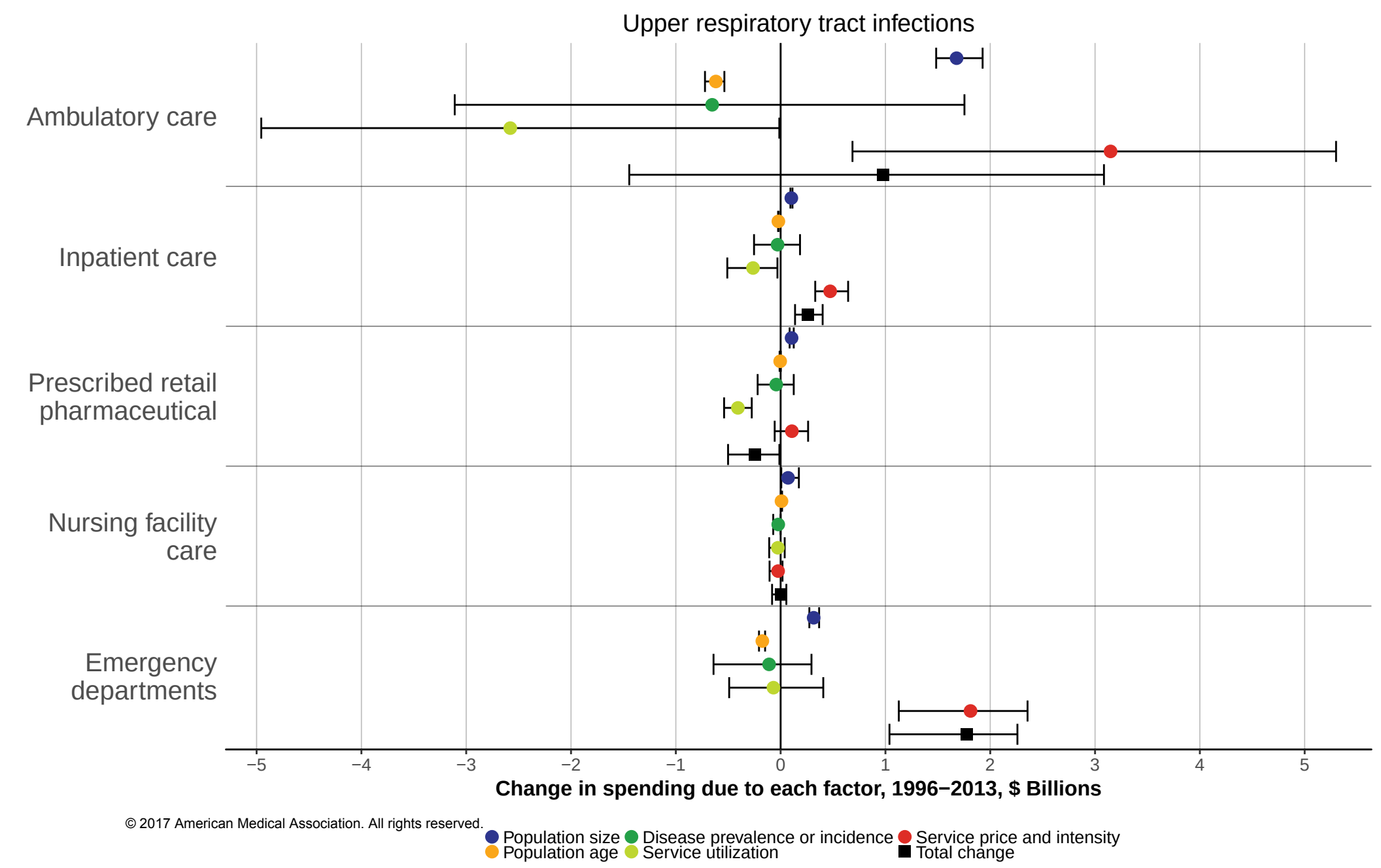
Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

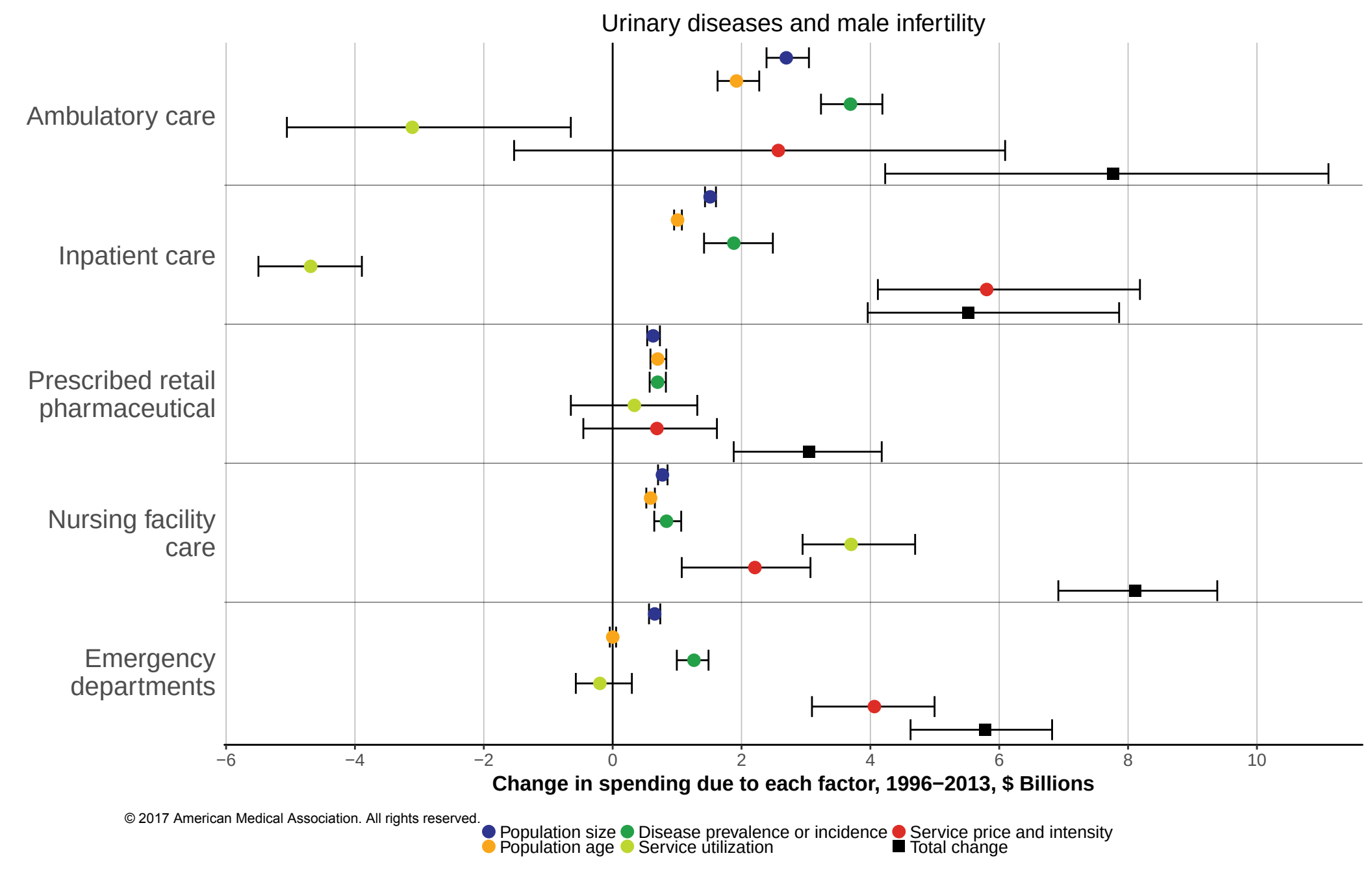


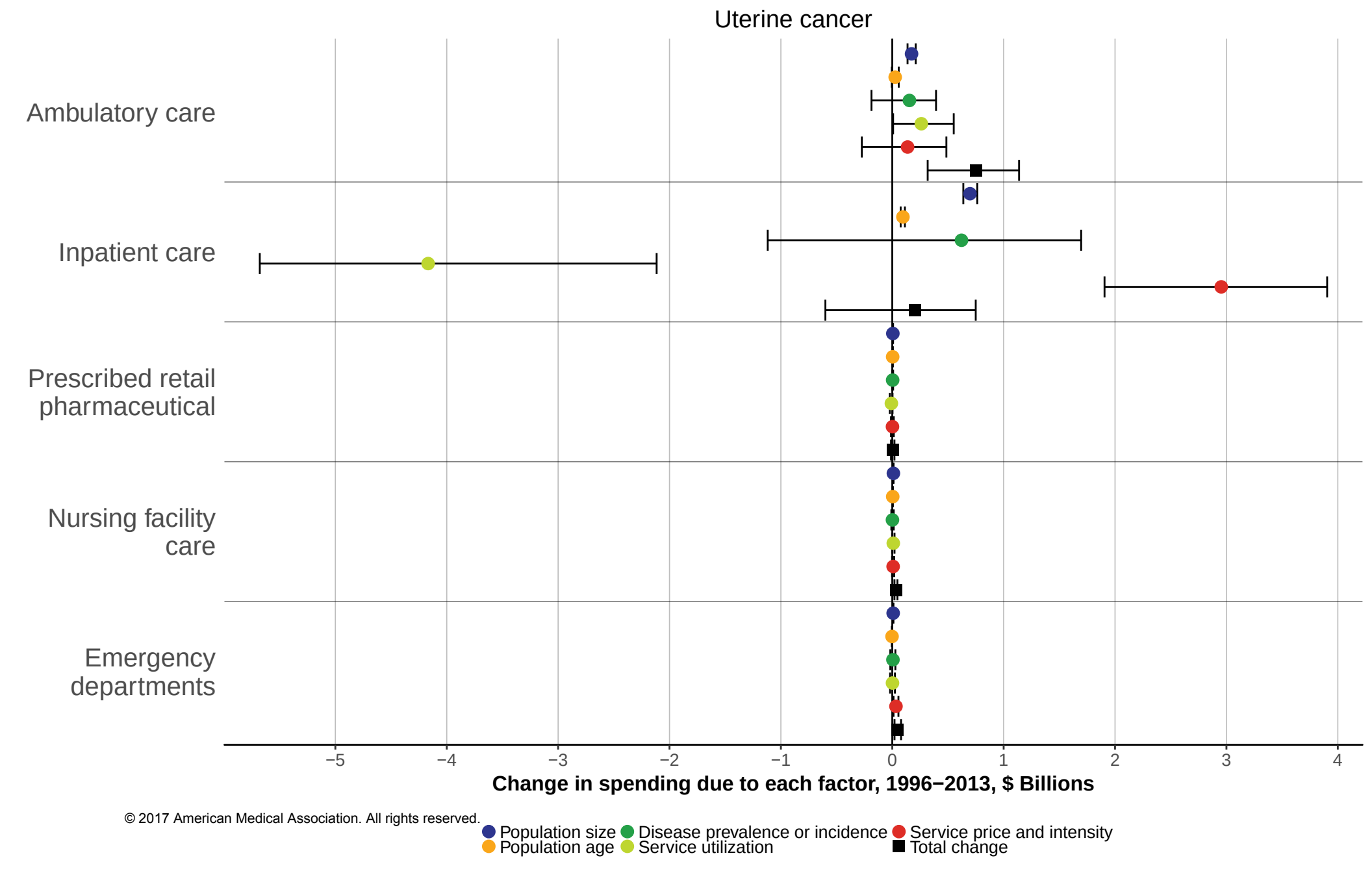


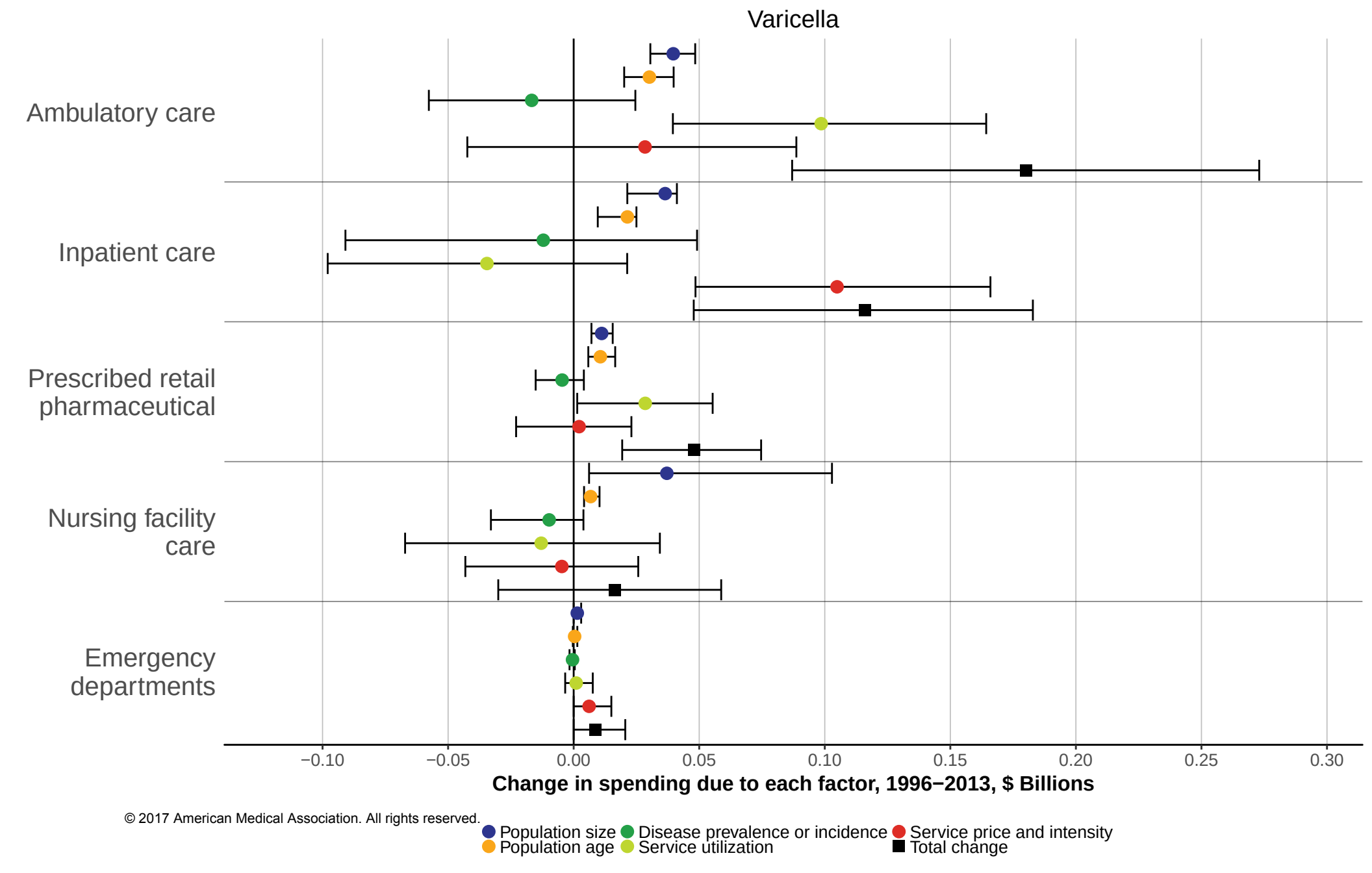


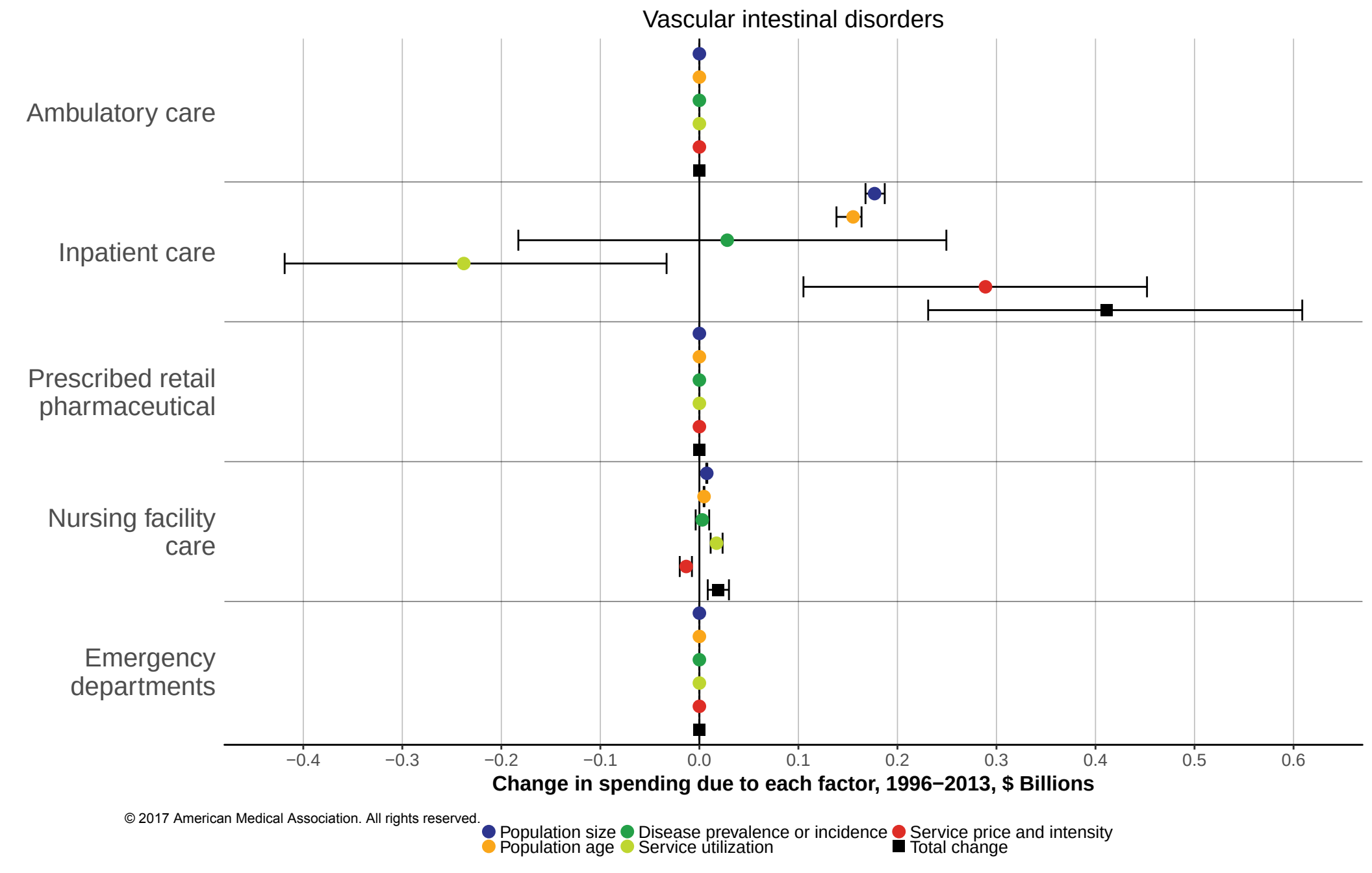


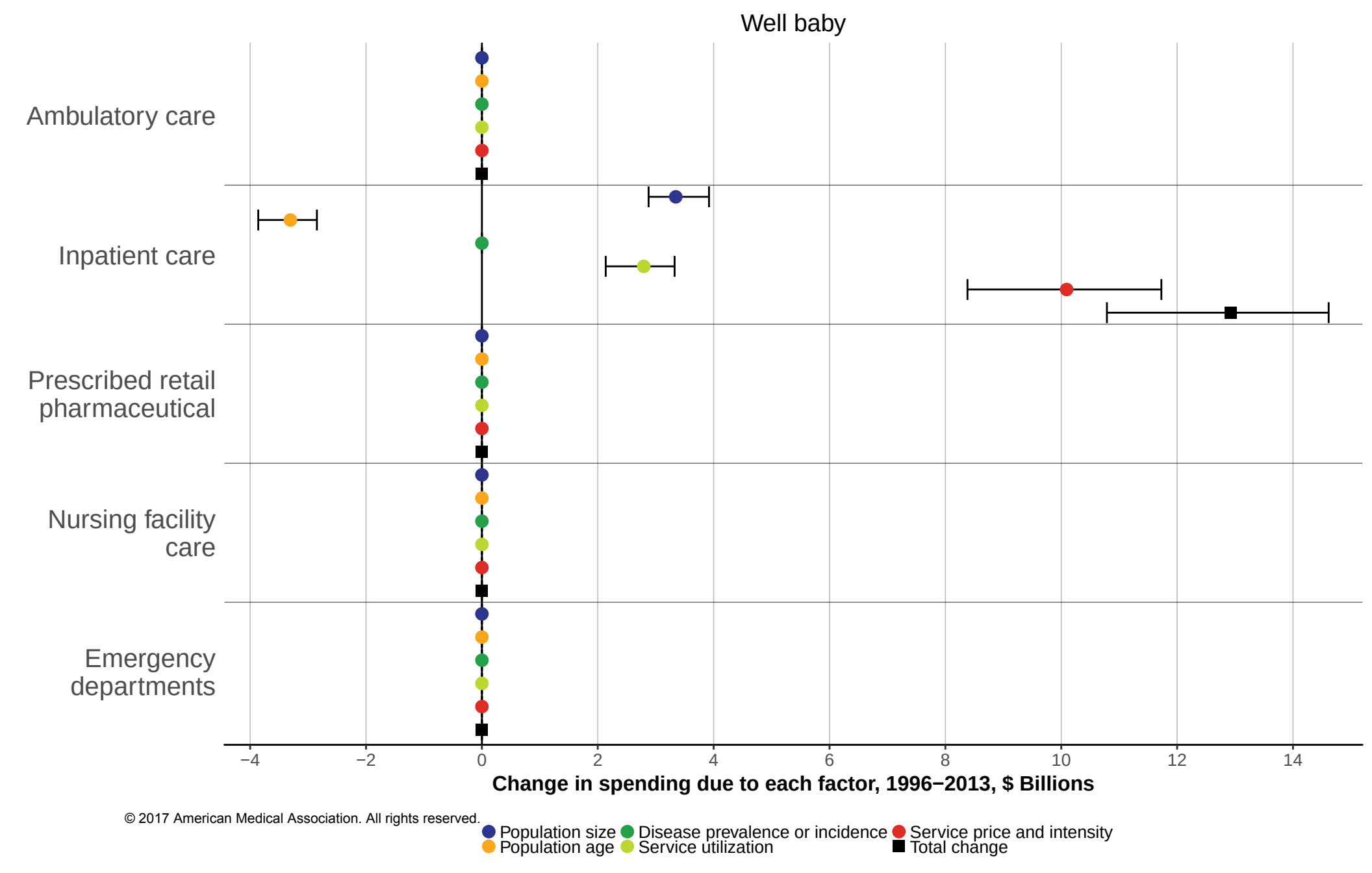


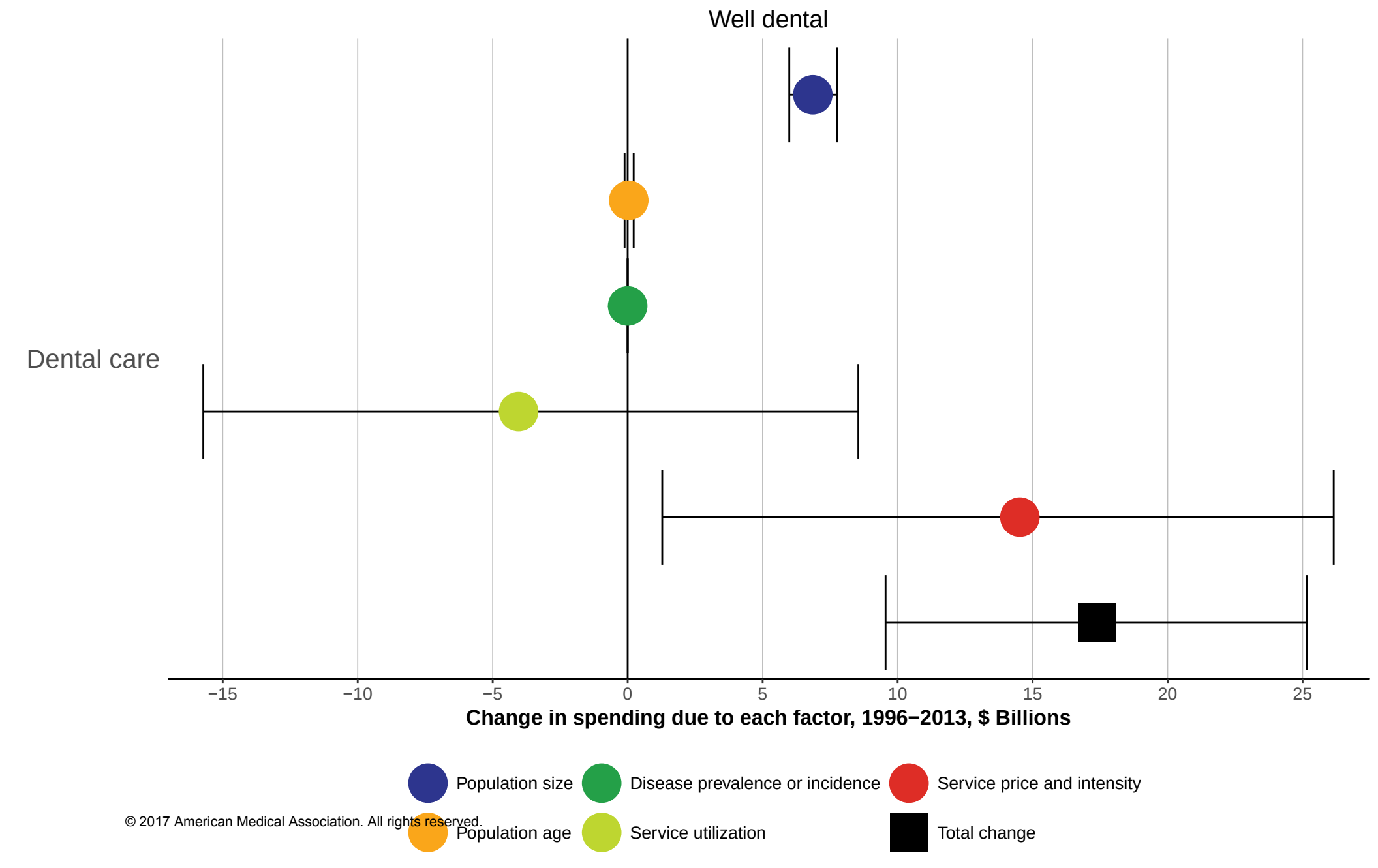


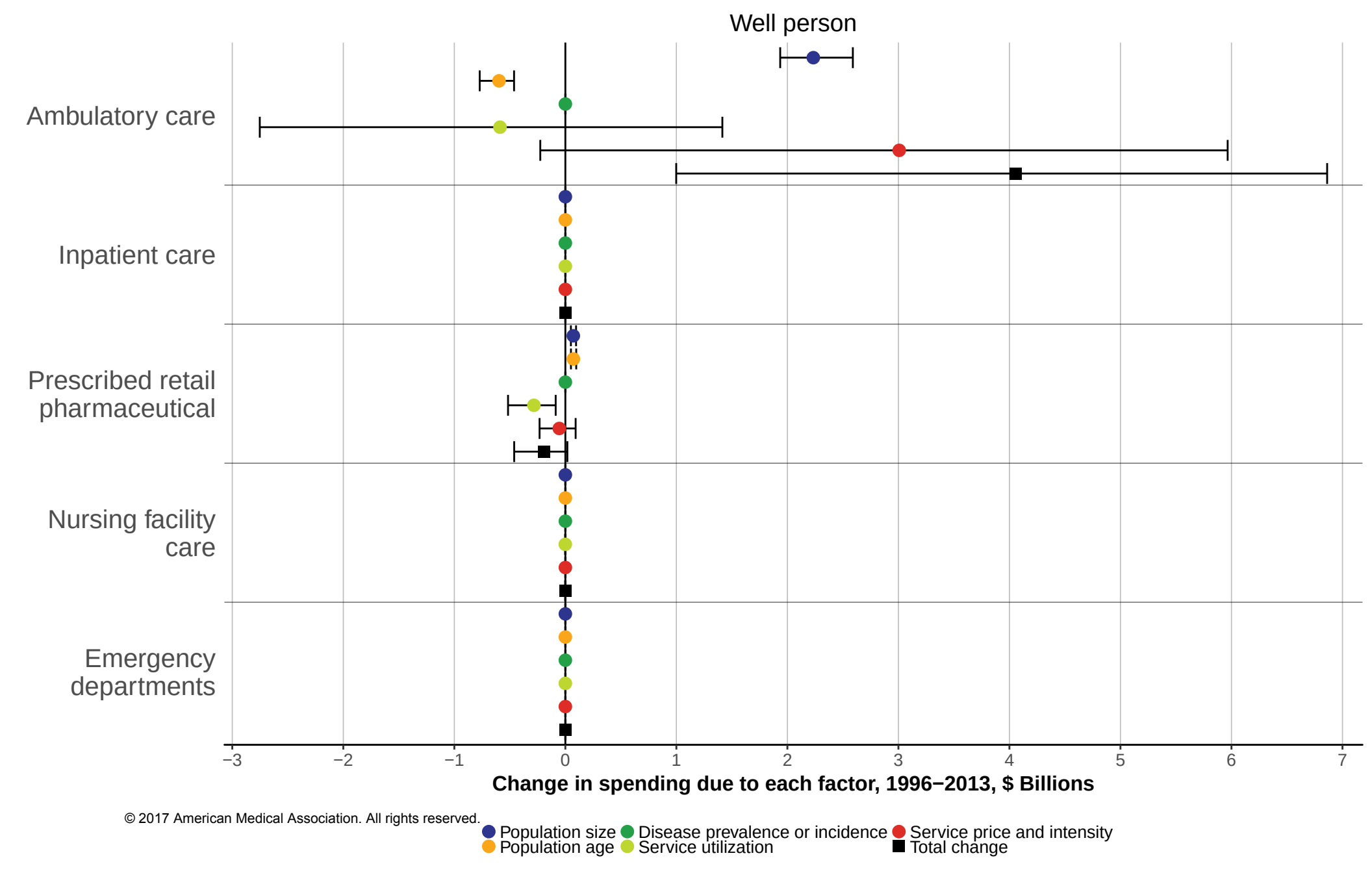


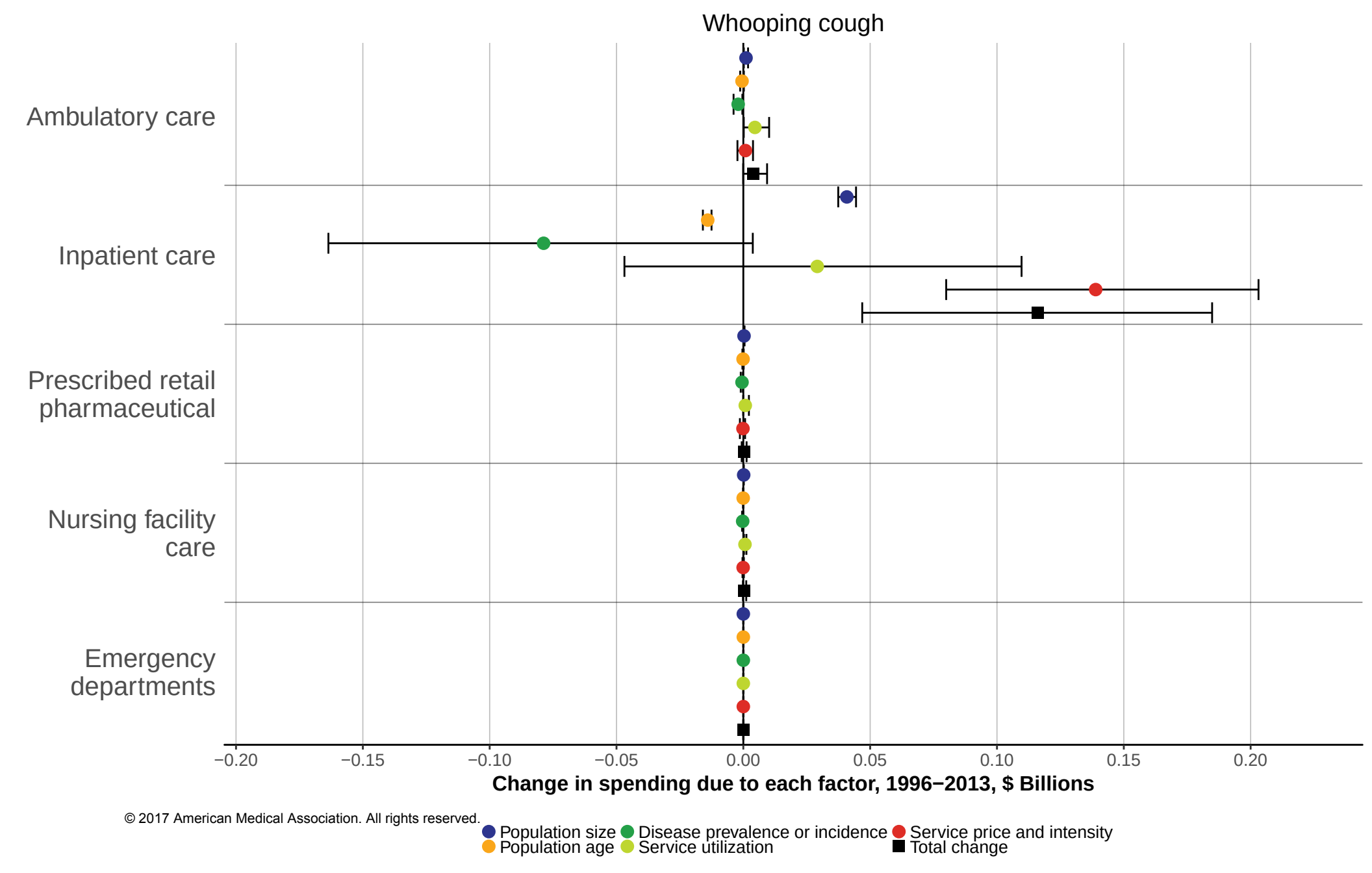












Population size
Disease prevalence or incidence
Service price and intensity
Population age
Service utilization
Total change

eReferences

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