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**UNCERTAINTY ABOUT PROJECTIONS OF
MEDICARE COST GROWTH**

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ABSTRACT

Over the next several decades, Medicare costs are going to increase significantly. Previous analysis has looked at the potential range of costs using a deterministic, scenario-based analysis. This provides a range of potential outcomes but provides no information as to the likelihood of these outcomes. The analysis here systematically considers the uncertainty inherent in forecasting Medicare costs using a Monte Carlo approach that reflects both the uncertainty in forecasting health costs and the uncertainty association with economic and demographic projections. Within 100 years, the 90 percent confidence interval for Medicare costs as a percent of GDP spans more than 30 percentage points

1. Introduction¹

Previous studies of the long-run outlook for Medicare have characterized the range of future costs by varying the rate of excess cost growth (the rate at which medicare costs per beneficiary exceeds growth in GDP per capita) and extrapolating into the future.² Although history is a useful guide for telling us what average excess cost growth might be, it provides no way of assigning probabilities to these high or low-cost paths. The approach used in this paper is to explicitly model the probability distribution for excess cost growth as well as other demographic and economic determinants of outlays. Stochastic simulation is then used to directly measure the probability distribution of future Medicare costs.³

The Congressional Budget Office (CBO) (2003) estimates that, in 2030, Medicare will account for between 5.7 and 11.5 percent of GDP.⁴ In 2050, that estimate rises to between 6.4 and more than 21 percent (2003). To put this in context, Medicare accounted for 2.6 percent of GDP in 2003 (Boards of Trustees, 2004). These ranges are developed by varying the long run excess cost growth rate. Under the intermediate cost scenario, a long run excess cost growth rate of 1 percent is assumed; that is, Medicare costs per beneficiary are assumed to grow 1 percent faster than GDP per capita. Under the low-cost scenario, Medicare costs are assumed to grow at the same rate as GDP per capita, and under the high cost scenario, an excess cost growth rate of

¹The author would like to thank John Sabelhaus and Michael Simpson of CBO's Health and Human Resources Division for their support and helpful comments.

²See for example, Congressional Budget Office (2003) or Boards of Trustees (2004).

³Lee and Miller (2002) follow a similar approach.

⁴Note that all costs are not net of premiums; that is, premiums have not been removed from the costs shown.

2.5 percent is assumed.⁵ While this approach estimates a range of possible outcomes, it provides no information as to the likelihood of those outcomes.

The Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds (“Boards of Trustees”) follow a similar approach with its high, low, and intermediate cost scenarios. Under each scenario, the complete set of inputs is varied together. Those inputs include the change in GDP per capita, the average wage in covered employment, the consumer price index, the real wage differential, the real interest rate, the total fertility rate, mortality rates, and health care costs. In the low-cost scenario, all inputs move to push the system toward lower costs. In the high cost scenario, the converse is true. Under the intermediate assumptions, Medicare costs are estimated to be 7.0 percent of GDP by 2030, 10.0 percent in 2050, and 13.9 percent by 2080.

In their 2004 report, the Boards of Trustees present a supplementary assessment of uncertainty in Part B Medicare cost projections. Only uncertainty in Part B cost growth is modeled stochastically, and other inputs remain deterministic. These results show that Part B costs could vary substantially from the intermediate projections.⁶

It is this potential for reality to vary significantly from a set of deterministic forecasts that makes stochastic analysis so useful. History is clearly a useful guide to what the future may look like, but it tells us nothing about the likelihood of future outcomes. Any stochastic simulation yields a scenario for which some chance exists that the set of exogenous inputs chosen will be

⁵See CBO (2003) for more details on the assumptions underlying these estimates.

⁶See Boards of Trustees (2004) for more details.

observed in the real world, and the likelihood of these outcomes will vary. Because the probability distribution for each input is assumed to have a bell-shaped distribution where values are likely to bunch around the expected value, repeated stochastic simulations will generate a distribution of outcomes that also exhibits bunching. The model can be solved many times making it possible to make inferences about the probability distributions of inputs and the resulting outputs.

This analysis focuses on developing a time series model for excess cost growth. The resulting time series equation, along with time series equations for other economic and demographic inputs, is then used to explicitly model the probability distribution of inputs used to forecast Medicare costs. The standard statistical tool for making inferences from historical data is time-series analysis, which uses historical data to project both the future values of variables and the variability around those future values. The resulting estimated equation (or set of equations) is used to generate expected future values simply by solving it forward through time.

Understanding excess cost growth and the likelihood of any given value is particularly important given the relative magnitude of growth attributable to the aging of the population and growth attributable to factors other than economic and demographic change. The portion of the increase in Medicare costs attributable to excess cost growth is larger than the portion attributable to the increasing number of Medicare beneficiaries and rising longevity (see Figure 1). This figure is derived deterministically using a long run excess cost growth rate of 1 percent. If 1 percent is too low, as has been the case historically, the relative importance of excess cost growth would be even greater. Further, understanding the likelihood of a given set of outcomes is an important advance in thinking about this issue.

This analysis shows that by 2100, Medicare costs as a percentage GDP could range from 7.9 percent up to 39.7 percent over a 90 percent confidence interval. This clearly is a large range of possible outcomes, and it is based on an expected long run excess cost growth rate of 1 percent. It also assumes a continuation of current Medicare law and no change in the factors influencing health care growth. The range of possible outcomes could be quite different if a long run excess cost growth rate of 1 percent proves to be incorrect. This highlights the importance of moving beyond the deterministic forecasts that researchers have typically produced to a stochastic approach that allows the likelihood of a range of outcomes to be formally evaluated.

2. Trends in Excess Cost Growth

Following the *Review of Assumptions and Methods of the Medicare Trustee's Financial Projections*, the Centers for Medicare and Medicaid Services (CMS) adopted a long run excess cost growth rate of 1 percent. This 1 percent figure is based on a careful analysis of growth in real national health expenditures per capita relative to growth in real GDP per capita. National health expenditures were chosen rather than Medicare costs alone because Medicare costs have been more heavily impacted by policy changes over the period of analysis than have total national health expenditures.⁷

Starting with data similar to that used by the Technical Review Panel on the Medicare Trustees Reports, the analysis presented in the Medicare Technical Panel Report is replicated and

⁷Data on national health expenditures are available from CMS at <http://www.cms.hhs.gov/statistics/nhe/default.asp>.

updated.⁸ The analysis is then repeated using a methodology that adjusts for the changing age and sex composition of the population.⁹ These adjustments and the different methodology do not substantially alter the general results, even though changes in per capita health expenditures vary by age group from 1987 to 2000. Data from the Medical Expenditure Panel Survey (MEPS) for 2000 and the National Medical Expenditure Survey (NMES) for 1987 are used to calculate average health expenditures by age group.¹⁰ Note that expenditures for children less than a year old are omitted.¹¹ The highest percentage change was for 30 to 39 year olds, and the smallest was for the 13 to 18 year olds (see Figure 2).

Much research has been done to attribute the growth in health care costs to its underlying components (see Weisbrod (1991), Newhouse (1992), Peden and Freeland (1995), and Jones (2002)), and the general consensus is that the technological change is the primary contributing factor. Jones quantifies the amount attributable to technology as 50 to 75 percent of the increase in health expenditures as a percentage of GDP. Peden and Freeland attribute 70 percent of the 373 percent growth in real per capita medical spending from 1960 to 1993 to “two technology-inducing” variables: the level of insurance coverage and noncommercial medical research spending. The current paper does not focus on the reasons for growth in health care costs and instead concentrates on analyzing the growth itself.

⁸See Chapter III of *Review of Assumptions and Methods of the Medicare Trustees' Financial Projections* (December 2000) for more detail.

⁹The Medicare technical panel elected not to make any adjustments for age and gender arguing that such adjustments would not substantially affect the results.

¹⁰Data for total medical expenditures are used, and results are weighted using the person weight provided with the data. Data for 1987 are adjusted using the algorithm provided in Zuvekas and Cohen (2002) to make the 1987 data comparable to the 2000 data.

¹¹Data for infants in 1987 are dominated by a small number of extremely high cost patients.

To perform this analysis, excess cost growth needs to be backed out from total cost growth and the trends need to be estimated. The ultimate goal is to develop an excess cost growth series and associated probability distribution to forecast Medicare costs. Data on national health expenditures are used rather than historical Medicare costs, which provides both a longer time series for analysis and abstracts from policy changes that have significantly impacted Medicare costs since its inception.

For purposes of this paper, excess cost growth (x_t) refers to any unexplained growth in national health expenditures (H_t/H_{t-1}) after accounting for growth in per capita GDP (GDP/N) and changes in the age and sex distribution in the population (specifically, growth in the population by age and sex (n_{as}) multiplied by an age-sex index (γ_{as})). In other words, this is all growth not accounted for by economic and demographic change. Specifically,

$$x_t = \frac{H_t}{H_{t-1}} * \frac{\sum_{as} n_{as(t-1)} * \gamma_{as(t-1)}}{\sum_{as} n_{ast} * \gamma_{ast}} * \frac{GDP_{t-1} / N_{t-1}}{GDP_t / N_t}$$

Excess cost growth is calculated for 1951 through 2002.

To develop a complete set of indices (γ_{as}) for all age and sex groups, a data set containing health expenditure data for all ages is needed. The spending indices used in this analysis are calculated using the NMES for 1987 and the MEPS for 1996 through 2000.¹² For each year, average total medical expenditures are calculated for each age and sex group. To create the index, the reference person is a 40-year-old male. For years prior to 1987, the age-sex profile is

¹²See Sabelhaus, Simpson, and Topoleski (2004) for a discussion of the impact of including time until death in Medicare spending indices. The general conclusion is that the addition of time until death does not significantly change forecast results.

assumed to equal that for 1987. Between 1996 and 2000, the indices exhibit a large amount of volatility, and so rather than using each year of data separately, the indices are averaged across years.¹³ Those averages are used for each year from 1996 through 2000 and for all years after 2000. For 1988 through 1995, the indices gradually move from the 1987 level to the average for 1996 to 2000.

The excess cost growth rates are largely consistent with the results presented in the Medicare Technical Panel report for the gap between growth in real GDP per capita and growth in real national health expenditures per capita even though the methodology is different. The numbers presented are based on ten-year rolling averages, which is consistent with the approach taken by the Medicare Technical Panel (see Table 1). Note that both real GDP and real national health expenditures are deflated using a CPI index.¹⁴ To create per capita figures, these numbers are divided by total population.

Looking instead at the annual variation in excess cost growth, the mean is slightly lower than the ten-year rolling average at 3.1 percent (see Table 2). The median is higher at 3.2 percent. The minimum is actually negative at -4.0 percent. Clearly, excess cost growth is a highly volatile measure. Annual changes in GDP and national health expenditures per capita follow the same basic pattern as the ten-year rolling averages, but there is greater variation in the series.

¹³The volatility could be because of time series variation, but it also could be attributable to sampling variation. MEPS documentation notes that MEPS expenditure estimates are especially sensitive to sampling variation because of the “underlying skewed distribution of expenditures.” (Agency for Healthcare Research and Quality, 2004)

¹⁴This is consistent with the approach taken for the Medicare Technical Panel Report although the text accompanying their Table 4 indicates that they adjust for general price inflation using a chain-weighted GDP price index.

The calculated excess cost growth rate is very sensitive to the years included in the analysis (see Table 3). The excess cost growth rate has clearly accelerated in recent years, and so when calculated through 2002 rather than through 1999, the last year of data available to the Medicare Technical Panel, the averages are higher. Between 2000 and 2002, the average annual excess cost growth rate exceeds 5 percent regardless of the calculation method.

This faster growth in health care costs is well documented. In fact, 2002 marked the sixth consecutive year of faster growth in national health expenditures with expenditures growing 9.3 percent in 2002. The average from 1990 through 2000 was 6.5 percent (Sethi and Fronstin, 2004). By 2002, national health expenditures accounted for 14.9 percent of GDP. This is up from 2000 levels of 13.3 percent, where it had hovered since 1993 (Levit et al., 2004). Levit et al. note that this growth is largely driven by a rebound in the growth of hospital spending.

3. Estimating a Probability Distribution for Future Excess Cost Growth

The results presented in this paper are projected using a model that combines a stochastic-demographic model with a model designed to forecast overall government expenditures, including Medicare costs.¹⁵ The goal of the stochastic macro-demographic model is to generate values for the economic and demographic inputs to the budget forecasting model in a Monte Carlo setting. The basic approach involves using standard time-series techniques applied to the stochastic inputs as in Frees et al. (1997) and Chang and Cheng (2002).¹⁶ The demographic

¹⁵For more details, see O'Harra et al. (2004).

¹⁶For more details on other time series processes used in forecasting future Medicare costs, see Congressional Budget Office, 2001.

inputs are the rate of mortality improvement across detailed age and sex groups, the overall fertility rate, and the level of immigration. The economic inputs for the budget model are real wage growth, inflation, the unemployment rate, interest rates, and rates of disability incidence and termination. The goal of the macro-demographic model is to create realistic stochastic variation in the annual values for each input, including correlations between those variables.

The stochastic macro-demographic model starts with Social Security Administration (SSA) intermediate projections to set central tendencies for each of the economic and demographic inputs. The SSA intermediate values are based on extrapolating historical averages for (generally) stationary processes like wage and price growth rates, and in that sense is consistent with the underlying time-series analysis used to build the macro-demographic model used here. Most of the stochastic inputs are treated as independent time-series processes, though inflation, unemployment, and interest rates are modeled together in a vector auto-regression (VAR). In all cases, the specifications were chosen using standard time-series techniques (CBO, 2001). Note that while this all of the stochastic inputs are discussed here, the most important when forecasting Medicare costs is excess cost growth.

Demographic Inputs

The three demographic models are all estimated using data from the Social Security Administration (see Table 4). Mortality improvement is modeled as an auto regressive (AR(1)) process for each of 42 separate age-sex groups.¹⁷ The data are available back to 1900. Although

¹⁷In the language of time series econometrics, a process is described in terms of its “AR” and “MA” properties, with “AR” denoting how many lagged terms are included in the equation and “MA” denoting how long the moving average is for the error terms. The simplest equation is an “AR(1)” which has only one lagged term and no

the equations are estimated separately, the rates of mortality improvement across age groups are correlated because the vector of innovations is drawn from a multivariate normal distribution estimated using the historical error terms, which are correlated. The overall fertility process is characterized as an ARMA(4,1) model estimated on data back to 1917. Identifying a stationary characterization for the fertility process is somewhat complicated by distinct breaks in the series at various points in history, notably at the end of the baby boom. Experiments with an alternative to the ARMA representation (a first-difference model) did change implied fertility dynamics, but the effect on variability in system finances was modest (CBO, 2001). Finally, the immigration process is also dominated by distinct breaks in the time-series at various points in history, but in this case, because of changes in policy. Again, the ARMA(4,1) representation is most appropriate for immigration.

Economic Inputs

Three of the four economic variables (inflation, unemployment, and the interest rate gap) passed the test for inclusion in a vector auto-regression (VAR). The VAR model uses two annual lags for each of the three variables and is estimated using data from Bureau of Labor Statistics (BLS) and the Social Security Administration for the period 1954-1999.

Unemployment rates are transformed using a log-odds ratio prior to estimation so the predicted values are constrained to the zero-one range in all cases. Total factor productivity is a white

moving average. The most complicated process is an “ARMA(4,1),” meaning there are four lagged terms and a single-period moving average of errors.

noise process. The standard deviation of the innovations is computed using data for 1950 through 2000.

The last two inputs to the long-term budget model are Social Security disability incidence and termination. Finding reasonable equations for variation in disability incidence and termination rates is made difficult because consistent data only exist back to 1975, and is further complicated because of changes in policy (stated and implicit) with respect to eligibility for the program. The problem is similar to the fertility model; there are clear breaks in the data that are (ex post) explainable, but it is not clear how to use that information when predicting future variability. Because there is no clear signal from the data, both models are specified as simple AR(1) processes.

Medicare Excess Cost Growth

The variation in excess cost growth is also estimated using an AR(1) process such that

$$x_t = 2.123 + 0.367x_{t-1} + \epsilon_t$$

(0.577) (0.126)

where x_t is excess cost growth and ϵ_t represents the random variable that describes the annual random shocks to excess cost growth. Standard errors are in parentheses. The standard deviation of the annual random shocks is 3.044. The p-value for the Dickey-Fuller test is 0.0002, indicating the rejection of the presence of a unit root. The results of the Ljung-Box test for white noise of the residuals indicate that there is no autocorrelation of the residuals.

A Monte Carlo simulation procedure is used to produce those probability distributions for future outcomes. The procedure involves making repeated random draws from values for annual

shocks, and the values for these annual shocks are entered into a time series equation, which generates a time path for excess cost growth. By repeating this process many times, inferences can be drawn about the probability distribution of future outcomes. In the case of excess cost growth, an expected value of 1 percent is assumed as opposed to using the expected value from the historical series. This assumption is consistent with the intermediate projections of the Boards of Trustees and consistent with previous CBO studies. In constructing the distribution of excess cost growth rates, a calculated deviation is added to this assumed expected value.

This process results in excess cost growth rates that vary quite considerably around the long term assumed mean of 1 percent (see Figure 3). The 90 percent uncertainty bands for the projection of excess cost growth cover a range of between -5 percent to over 6 percent annually. The range for average values narrow considerably to 2.5 percentage points in total. Note that average uncertainty bands show the 90 percent confidence range for the average of 2004 through a given year; the annual uncertainty bands show the 90 percent confidence interval for a given year. The figure shows results for aggregate excess cost growth, while the forecasting model uses category-specific excess cost growth rates. In the long run, however, all excess cost growth rates are assumed equal.

The forecast is shown as aggregate Medicare costs as a percentage of GDP, but underlying this aggregate forecast is a set of category-specific cost forecasts. Each category of costs, which include inpatient hospital, outpatient hospital, skilled nursing facilities, home health services, hospice care, physicians and other Medicare Part B services, and prescription drugs, has its own excess cost growth rate. For each category of costs, excess cost growth rates are calculated separately for the early years of the forecast. In the long run, assumed excess cost

growth rates for each category are 1 percent. As described above, this is consistent with the assumption made by the CMS actuaries. Between the short and long run, the excess cost growth rates slowly phase in to the long term rates. The same time series equation is used to develop a distribution for each excess cost growth rate, however. Lack of data on a category-specific basis prevented the estimation of separate time series equations for each excess cost growth rate. The same stochastic draw is used to predict each excess cost growth series in each year.

Using this approach rather than one where the assumed long run excess cost rate is fixed allows a probability distribution of outcomes to be calculated. It also allows excess cost growth to vary annually (around a predetermined mean). Looking back historically, excess cost growth has been a highly variable series. Using this approach, some of that variability is allowed to continue.

4. Stochastic Analysis of Future Medicare Outlays

Looking at a 90 percent confidence interval based on the results from one thousand Monte Carlo simulations, Medicare costs range from 5.6 percent of GDP at the fifth percentile to 16.3 percent at the ninety-fifth percentile in 2050. As the years progress, this range increases, and so by 2075, this range has increased to 6.7 percent of GDP at the fifth percentile and 24.9 percent at the ninety-fifth. By 2100, this range has increased still further to between 7.9 percent and 39.7 percent. The range of possible outcomes widens significantly as the forecast period gets longer (see Figure 4). The median is also shown in the figure, and this closely mirrors the results of a deterministic simulation. Even at the median, Medicare costs as a percentage of GDP exceed 20 percent within 100 years.

These stochastic projections assume that a 1 percent excess cost growth rate is the most likely future outcome, and so they should be viewed with that in mind. Should actual future excess cost growth differ from that 1 percent, the distribution would shift. Using this assumption, the range of possible outcomes is narrower than CBO predicts in 2050.

These projections assume a continuation of current Medicare policy and no change in the factors driving health care costs. A substantial rise in Medicare costs as a share of GDP could induce changes in the policy environment or in the factors that drive health care costs. The chances of this occurring are clearly asymmetric. If Medicare costs were to increase gradually, changes in the health care environment would be less likely. Health care costs increasing to a much larger share of GDP may trigger changes to the extent that the increase forced reduced consumption of other goods and services. Estimates of the behavioral response to large increases in health care spending are beyond the scope of this paper.

5. Conclusion

Medicare costs as a percentage of GDP are expected to increase significantly as the baby boom generation ages. Health care costs under current law are expected to continue to grow more quickly than GDP, as the number of Medicare beneficiaries grows with the impending retirement of the baby boomers. Uncertainty is inherent in any long term forecast. This paper treats the uncertainty in the long term growth of health costs systematically, in addition to the systematic treatment of uncertainty in other economic and demographic inputs. Specifically, fertility, mortality, and GDP all vary stochastically and feed directly into the calculation of

Medicare costs. This analysis shows the uncertainty associated with projections of Medicare costs as a percentage of GDP.

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Table 1
Summary Statistics for Trends in National Health Expenditures and GDP, 1951-2002
Based on Ten-Year Rolling Averages

	Real NHE Per Capita	Real GDP Per Capita	NHE-GDP	Excess Cost Growth
Average	4.5%	1.8%	2.7%	3.4
Median	4.4	1.6	2.9	2.9
25 th Percentile	3.7	1.3	2.5	2.5
10 th Percentile	3.1	1.1	1.9	2.0
Minimum	2.6	0.4	1.0	1.7

NOTE: Column (1) less column (2) may not equal column (3) as the median and other statistics are selected separately in each case. Excess cost growth is adjusted for age and sex.

Table 2
Summary Statistics for Trends in National Health Expenditures and GDP, 1951-2002
Annual Changes

	Real NHE Per Capita	Real GDP Per Capita	NHE-GDP	Excess Cost Growth
Average	4.3%	1.8%	2.5%	3.1%
Median	4.2	2.0	2.3	3.2
25 th Percentile	3.0	0.4	0.6	0.7
10 th Percentile	1.8	-2.2	-0.8	-1.1
Minimum	0.2	-5.0	-4.4	-4.0

NOTE: Column (1) less column (2) may not equal column (3) as the median and other statistics are selected separately in each case. Excess cost growth is adjusted for age and sex.

Table 3
Excess Cost Growth: Average Annual Growth Rates for Selected Time Periods

	Real NHE per capita	Real GDP per capita	NHE-GDP	Excess Cost Growth
1951-2002	4.4%	1.7%	2.6%	3.1%
1960-2002	4.5	1.8	2.6	3.4
1970-2002	3.9	1.5	2.4	3.5
1980-2002	3.9	1.5	2.5	4.3
1990-2002	3.1	1.3	1.8	4.3
2000-2002	5.6	0.0	5.6	5.9

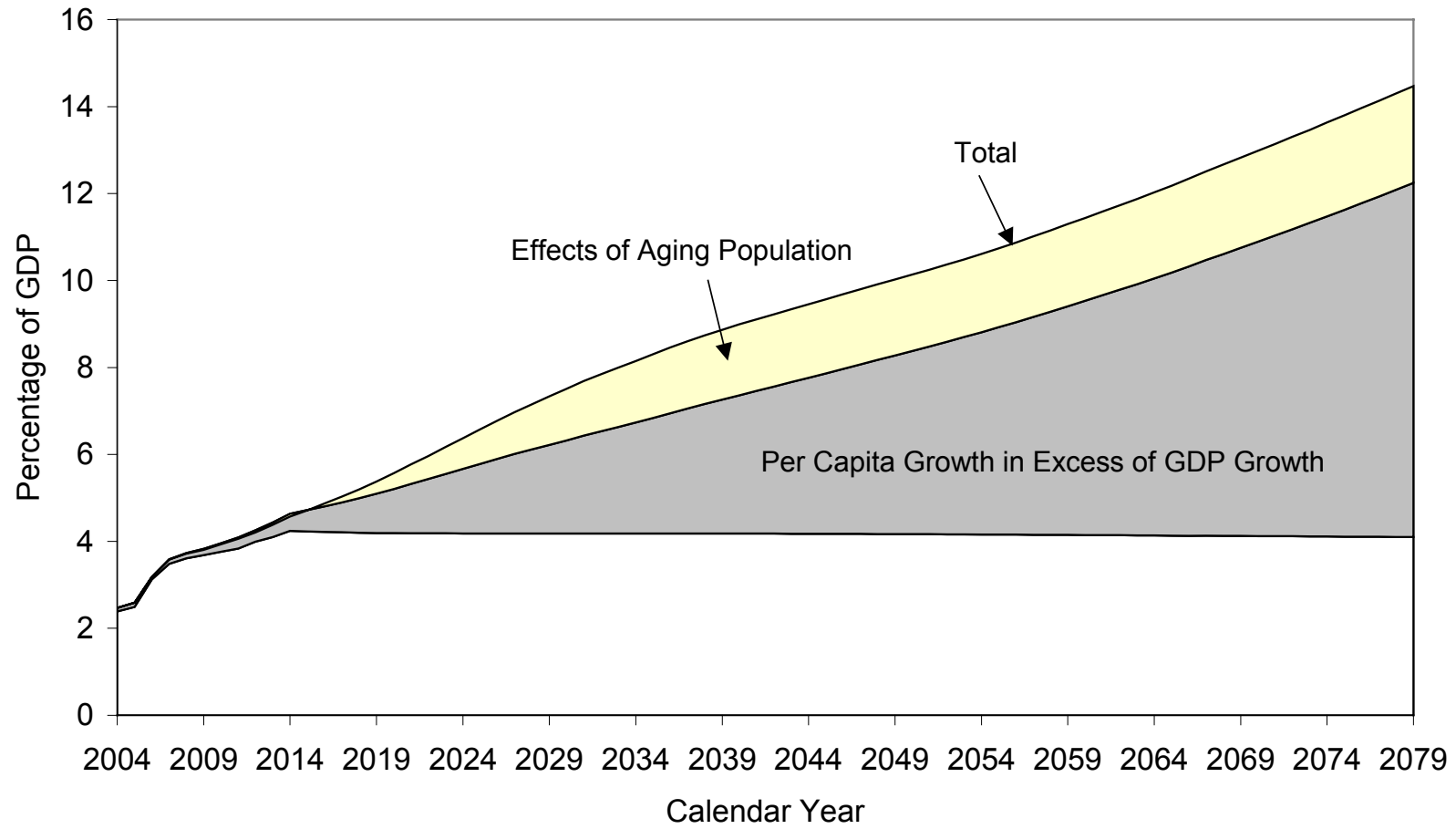
NOTE: Excess cost growth is adjusted for age and sex.

Table 4
Equations in Stochastic Macro-Demographic Model

<i>Variable</i>	<i>Description of Stochastic Process</i>
Mortality Improvement	Separate AR(1) equations for each of 21 age and 2 sex groups estimated using SSA data for 1900-1995. Model draws correlated errors across 42 groups using multi-variate normal distribution.
Fertility	ARMA(4,1) equation for overall fertility rate estimated using SSA data for 1917 through 1997.
Immigration	ARMA(4,1) equation for total immigration estimated using SSA data for 1901 through 1995.
Unemployment	VAR model with two lags each on unemployment, inflation, and real interest gap estimated using BLS and SSA data for 1954 through 1999.
Inflation (CPI-W)	VAR model with two lags each on unemployment, inflation, and real interest gap estimated using BLS and SSA data for 1954 through 1999.
Total Factor Productivity	A white noise process; standard deviation of innovations is computed using data for 1950 through 2000.
Interest Rate Gap	VAR model with two lags each on unemployment, inflation, and real interest gap estimated using BLS and SSA data for 1954 through 1999.
DI Incidence	AR(1) model for overall DI incidence rate estimated using SSA data for 1975 through 1999.
DI Termination	AR(1) model for overall DI termination rate estimated using SSA data for 1975 through 1999.

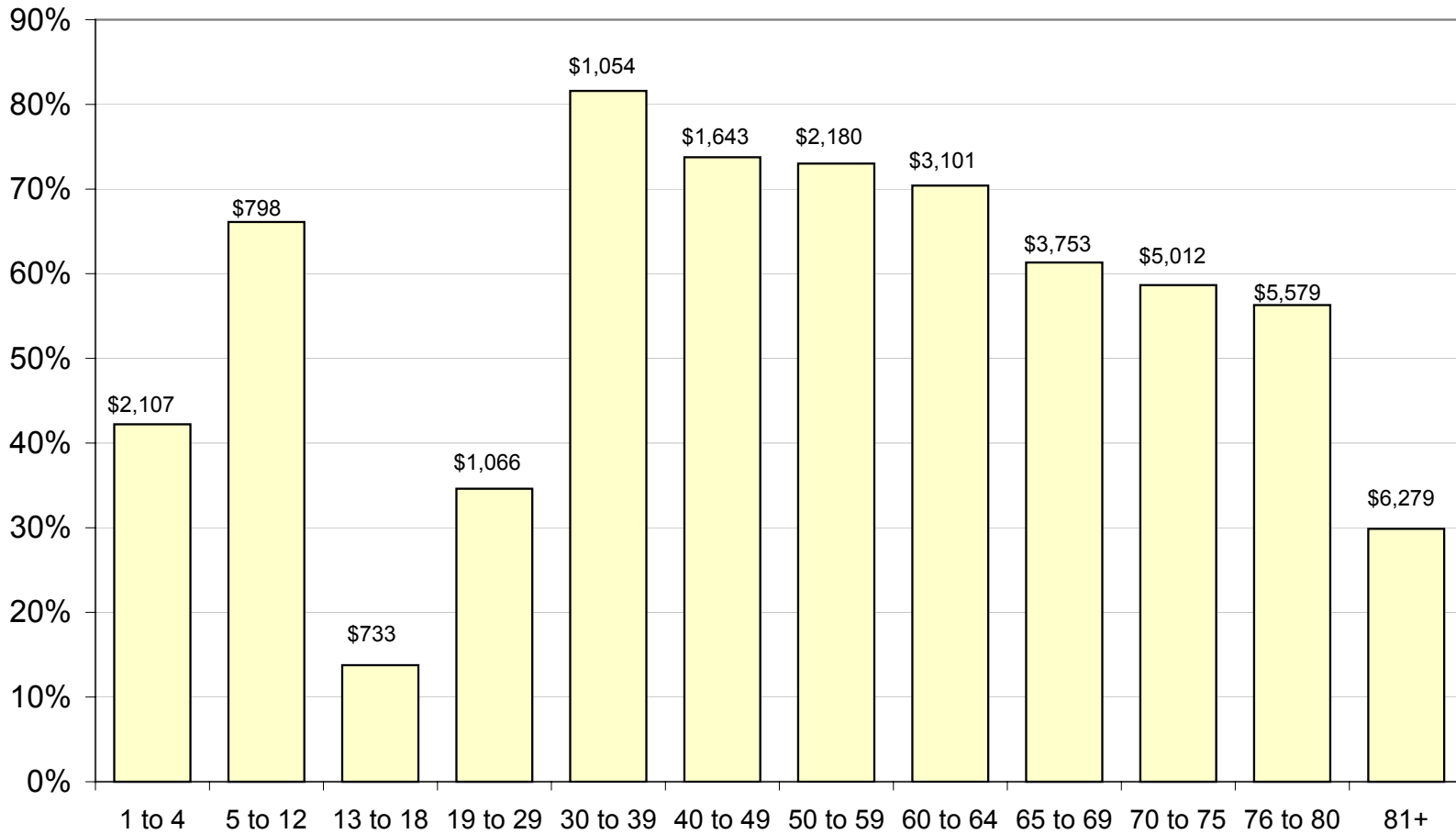
In the language of time series econometrics, a process is described in terms of its “AR” and “MA” properties, with “AR” denoting how many lagged terms are included in the equation and “MA” denoting how long the moving average is for the error terms. The simplest equation is an “AR(1)” which has only one lagged term and no moving average. The most complicated process is an “ARMA(4,1),” meaning there are four lagged terms and a single-period moving average of errors.

Figure 1
Effects of Aging and Excess Cost Growth



SOURCE: Author's calculations

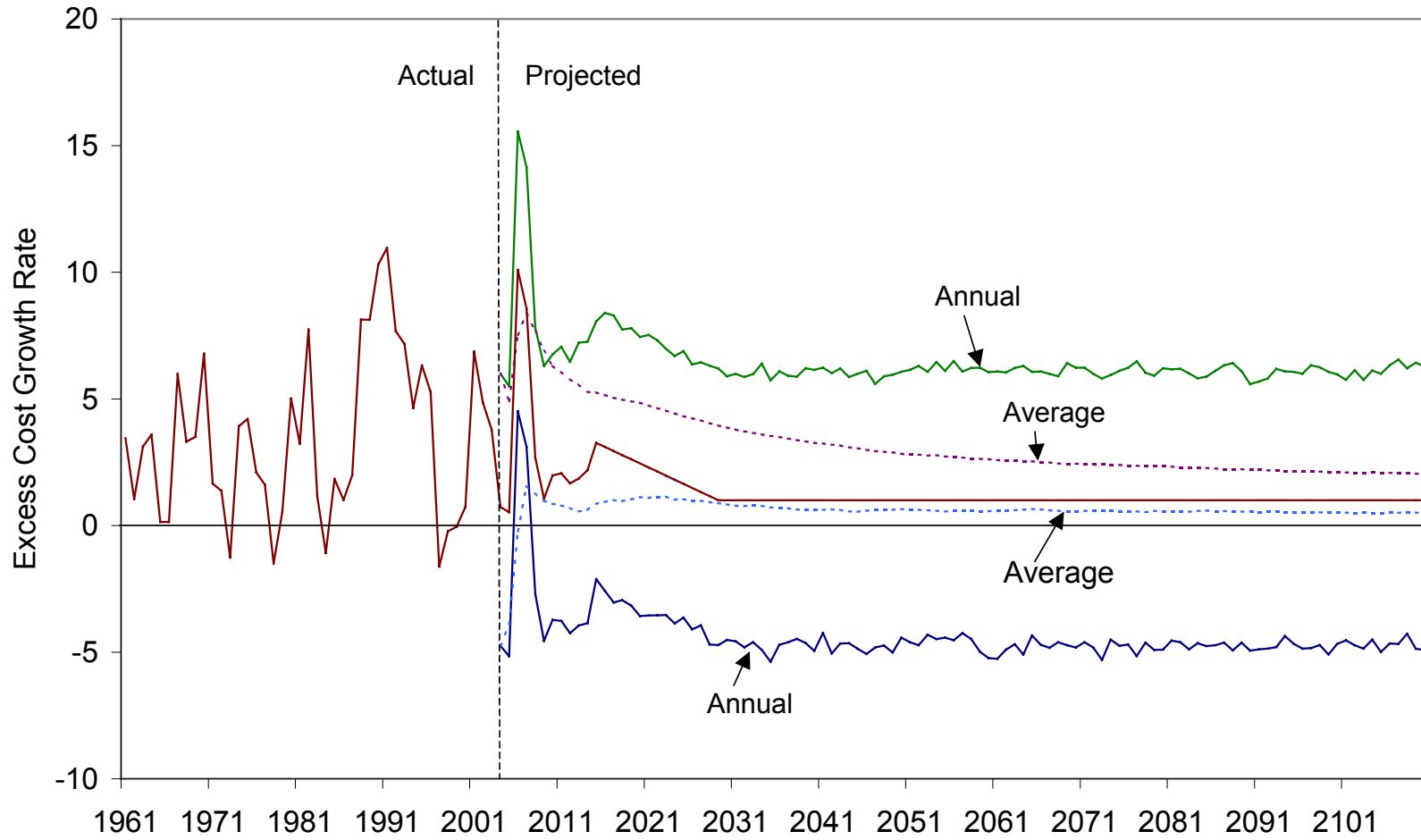
Figure 2
Percentage Change in Per Capita Health Care Expenditures, 1987 to 2000



SOURCE: Author's calculations

NOTE: Compares data from 1987 NMES that have been adjusted to be comparable to later MEPS data (see Zuvekas and Cohen, 2002). Numbers above bars are 2000 average expenditures.

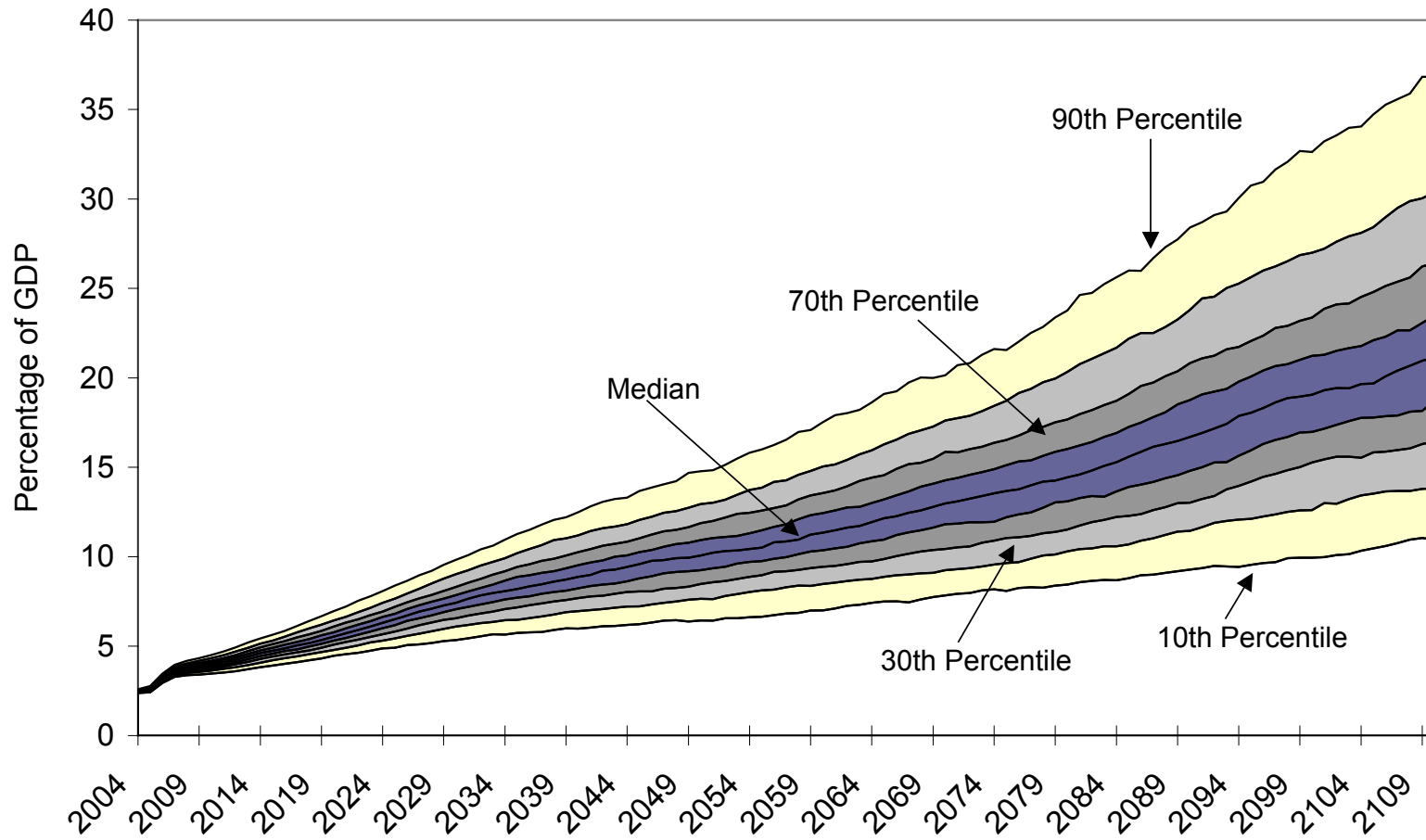
Figure 3
Uncertainty Bands for Medicare Excess Cost Growth



SOURCE: Author's calculations.

NOTE: Annual uncertainty bands show the 90 percent confidence range for a given year. Average uncertainty bands show the 90 percent confidence range for the average of 2004 through a given year. The center line shows deterministic excess cost growth.

Figure 4
Medicare Costs as a Percentage of GDP



SOURCE: Author's calculations.