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Why has longevity increased faster in some states than others?

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Abstract

The rate of increase in longevity has varied considerably across U.S. states since 1991. This paper examines the effect of medical innovation (changes in drug vintage), behavioral risk factors (obesity, smoking, and AIDS incidence), and other variables (education, income, and health insurance coverage) on longevity using longitudinal state-level data. This approach controls for the effects of unobserved factors that vary across states but are relatively stable over time (e.g. climate and environmental quality), and unobserved factors that change over time but are invariant across states (e.g. changes in Federal government policies). We also analyze interstate variation in productivity (output per employee) growth, and in the growth of per capita medical expenditure (total, and by type).

States in which the vintage of both self- and provider-administered drugs grew faster than average had above-average increases in life expectancy, whether or not we adjust for state-specific changes in the distribution of disease. Life expectancy grew more slowly in states with larger increases (or slower declines) in AIDS, obesity, and smoking rates. States with high income growth had *smaller* longevity increases.

States with larger increases in Medicaid drug vintage had faster productivity growth, conditional on income growth and the other factors. The increase in Medicaid drug vintage is estimated to have increased output per employee by about 1% per year. Much of this may be attributable to increased hours worked per employee.

Increases in income, education, smoking, and the incidence of AIDS tend to increase per capita medical expenditure; expanded health insurance coverage reduces it. States in which drug vintage has increased the most have not had above-average increases in overall medical expenditure. While use of newer drugs has increased some types of medical expenditure, it has reduced other types, and the expenditure reductions approximately offset the expenditure increases. Although use of newer drugs does not appear to have increased *annual* medical expenditure, it probably has increased *lifetime* medical expenditure, but the increase in lifetime medical cost per life-year gained from using newer drugs has been quite low.

The estimates indicate that the growth in obesity and the growth in income both reduced the growth in life expectancy. If obesity and income had not increased, life expectancy at birth would have increased by 3.88 years. The increases in Medicaid and Medicare drug vintage account for 2.43 years (63%) of the "potential increase" in life expectancy. The declines in AIDS incidence and smoking account for 0.23 and 0.12 (6% and 3%) of the potential increase in life expectancy, respectively. About 1.1 years (28%) of the potential increase in life expectancy at birth is unexplained. Differences in drug vintage explain some of the interstate variation in life expectancy, but the fraction of cross-sectional variance explained is smaller than the fraction of aggregate time-series variance (growth) explained.

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During the twentieth century, U.S. life expectancy at birth increased by almost 30 years (63%), from 47.3 years in 1900 to 77.0 years in 2000. (See Figure 1.) Nordhaus (2002) estimated that, "to a first approximation, the economic value of increases in longevity over the twentieth century is about as large as the value of measured growth in non-health goods and services" (p. 17). Murphy and Topel (2005) observed that "the historical gains from increased longevity have been enormous. Over the 20th century, cumulative gains in life expectancy were worth over $1.2 million per person for both men and women. Between 1970 and 2000 increased longevity added about $3.2 trillion per year to national wealth, an uncounted value equal to about half of average annual GDP over the period."

The rate of increase in longevity has varied considerably across states. Figure 2 shows the increase in life expectancy at birth during the period 1991-2004,[1] by state. In the eight states with the smallest increase, life expectancy increased by only 0.31-1.16 years. In the eight states with the largest increase, life expectancy increased by 2.5-4.3 years. This paper seeks to help answer the question, why has longevity increased faster in some states than other states?

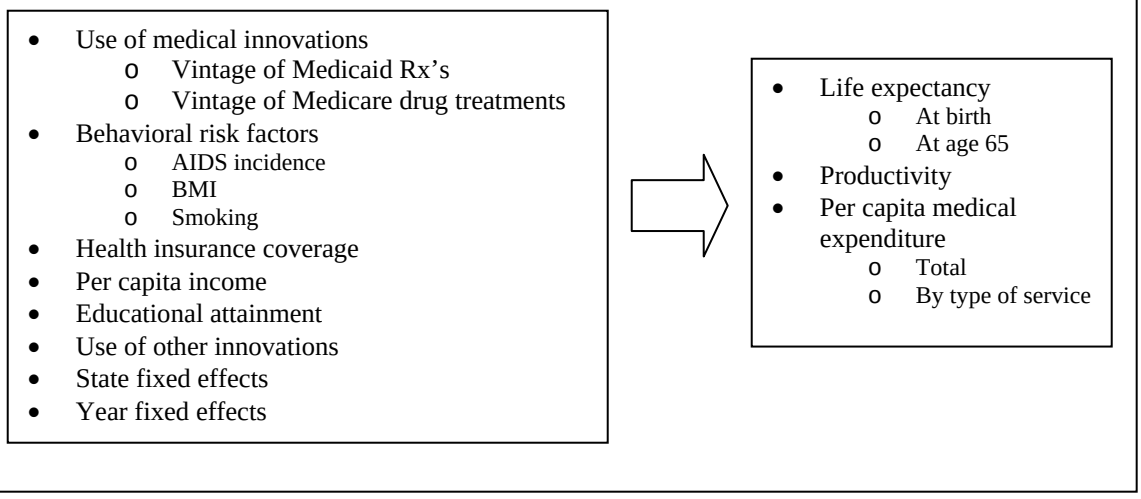
Longevity is likely to depend on a number of factors, including access to health care and medical innovations, exogenous changes in disease incidence (e.g. the appearance of new diseases such as HIV/AIDS), income, education, and behavioral risk factors (e.g., obesity and smoking). By analyzing longitudinal state-level data, we can measure and control for many of these factors. We can also control for the effects of unobserved factors that vary across states but are relatively stable over time (e.g. climate and environmental quality), and unobserved factors that change over time but are invariant across states (e.g. changes in Federal government policies).

In addition to interstate variation in longevity growth, we will analyze interstate variation in productivity (output per employee) growth, and in the growth of per capita medical expenditure (total, and by type, e.g. expenditure on physicians, prescription drugs, and hospital care). In particular, we will examine how medical innovation (use of newer medical products) has affected the level and structure of health expenditure.

[1] Due to limitations on available data, this paper will analyze changes in longevity during the period 1991-2004.

The overall conceptual framework of the paper is depicted in Figure 3.

Figure 3
Conceptual framework



Previous literature suggests that technological innovation in general, and new goods in particular, play a key role in economic growth. In Section I, we briefly survey this literature, discuss the measurement of medical innovation, including adjustment for state-specific changes in the distribution of disease, and consider why the rate of innovation may vary across states. Section II describes the econometric models we will estimate. Section III describes the data sources and presents some descriptive statistics. Empirical results are presented in Section IV. Implications of the estimates are discussed in Section V. The final section presents a summary and conclusions.

I. Innovation: literature review and measurement issues

While longevity is probably influenced by a number of factors, medical innovation—the use of new medical goods and services—is likely to play a pre-eminent role in explaining longevity growth. Economists believe that the development of new products is the main reason why people are better off today than they were several generations ago. Grossman and Helpman (1993) argued that "innovative goods are better than older products simply because they provide more 'product services' in relation to

their cost of production." Bresnahan and Gordon (1996) stated simply that "new goods are at the heart of economic progress." Jones (1998) argues that "technological progress [is] the ultimate driving force behind sustained economic growth" (p.2), and that "technological progress is driven by research and development (R&D) in the advanced world" (p. 89). Bils (2004) makes the case that "much of economic growth occurs through growth in quality as new models of consumer goods replace older, sometimes inferior, models."

The best way to measure utilization of medical innovations (embodied technological change) is to measure the mean *vintage* of medical goods and services used. The vintage of a good is the year in which the good was first used. For example, the vintage of the drug atorvastatin (Lipitor) is 1997—the year the drug was approved by the FDA. We seek to test the hypothesis that, ceteris paribus, people using newer, or later vintage, medical goods and services will be in better health, and will therefore live longer. This hypothesis is predicated on the idea that these goods and services, like other R&D intensive products, are characterized by *embodied technological progress*.[2]

A number of econometric studies (Bahk and Gort (1993), Hulten (1992), Sakellaris and Wilson (2001, 2004)) have investigated the hypothesis that capital equipment employed by U.S. manufacturing firms embodies technological change, i.e. that each successive vintage of investment is more productive than the last. Equipment is expected to embody significant technical progress due to the relatively high R&D-intensity of equipment manufacturers. The method that has been used to test the equipment-embodied technical change hypothesis is to estimate manufacturing production functions, including (mean) vintage of equipment as well as quantities of capital and labor. These studies have concluded that technical progress embodied in equipment is a major source of manufacturing productivity growth.

Although most previous empirical studies of embodied technical progress have focused on equipment used in manufacturing, embodied technical progress may also be

[2] Solow (1960, p 91): argued that "many if not most innovations need to be embodied in new kinds of durable equipment before they can be made effective. Improvements in technology affect output only to the extent that they are carried into practice either by net capital formation or by the replacement of old-fashioned equipment by the latest models…" We hypothesize that innovations may be embodied in nondurable goods (e.g. drugs) and services as well as in durable equipment.

an important source of economic growth in health care. One important input in the production of health—pharmaceuticals—is even more R&D-intensive than equipment. According to the National Science Foundation, the R&D intensity of drugs and medicines manufacturing is 74% higher than the R&D intensity of machinery and equipment manufacturing. Therefore, it is quite plausible that there is also a high rate of pharmaceutical-embodied technical progress.

Measuring vintage

The general definition of vintage we will use is:

$$vint_{it} = \frac{\Sigma_p \, freq_{pit} \, vint_p}{\Sigma_a \, freq_{pit}}$$

where

$vint_{it}$ = the mean vintage of products and services used in state i in year t
$freq_{pit}$ = the frequency of use of product or service p in state i in year t
$vint_p$ = the vintage (year of first use) of product or service p

In principle, we would like to measure the vintage of all drugs, all other medical goods and services, and even all other products and services. Unfortunately, this is not possible.

We will measure the mean vintage of outpatient prescription drugs paid for by the state's Medicaid program, and the mean vintage of drugs administered by providers (e.g., chemotherapy) to Medicare beneficiaries. The number of prescriptions paid for by Medicaid is very large: according to the Medical Expenditure Panel Survey, in 1997, Medicaid paid for about 201 million prescriptions—11% of all U.S. prescriptions. Moreover, we show in Appendix A that the extent of utilization of new drugs in the Medicaid program is strongly correlated with the extent of utilization of new drugs in general: the vintage of non-Medicaid (and all) rx's tended to increase more in states with larger increases in the vintage of Medicaid rx's.

Drugs administered by providers are quite different from self-administered drugs, and Medicare pays for a substantial fraction of the former. In 2004, Medicare paid

providers $7.6 billion for performing 522 million pharmaceutical procedures.[3] Medicare data on the frequency of use of non-pharmaceutical services (e.g. lab and surgical procedures) are also available. However, due to asymmetries in FDA regulation, determining the vintage of non-pharmaceutical medical services is far more difficult than determining the vintage of pharmaceutical products and procedures.

Since we will not control for the vintage of non-pharmaceutical medical services, and the latter may be correlated with drug vintage, the drug vintage coefficients we estimate may to some extent reflect the effect of other medical innovation as well as the effect of drug innovation. The coefficients could also reflect the effect of *non-medical* innovation, e.g. consumer use of information technology. We will attempt to control for the latter by estimating some models that control for the percent of state residents who use a computer at home.

Adjusting for state-specific changes in the distribution of disease

If there have been state-specific *changes* in the distribution of disease, and drug vintage is correlated with disease severity (e.g., newer drugs tend to be for less severe diseases), the coefficient on drug vintage could be biased. However, we can eliminate any potential bias by constructing an alternative (fixed-weighted) index of drug vintage.

Consider the following simplified model of life expectancy:

$$LE = \beta_1 V + \beta_2 S$$

where LE = life expectancy, V = drug vintage, and S = (mean) disease severity. Hence

$$\Delta LE = \beta_1 \Delta V + \beta_2 \Delta S$$

Suppose that $\beta_1 > 0$ and that $\beta_2 < 0$. For simplicity, suppose that there are just 2 diseases: a high-severity disease and a low-severity disease. Mean disease severity depends on the proportions of patients with each disease:

$$S = high\% \; S_H + (1 - high\%) \; S_L = S_L + (S_H - S_L) \; high\%$$

[3] Source: CMS, Medicare Part B Physician/Supplier Data by BETOS, Calendar Year 2004, http://www.cms.hhs.gov/MedicareFeeforSvcPartsAB/Downloads/BETOS04.pdf.

where high% = the percent of patients with the high-severity disease, S_H = severity of the high-severity disease, S_L = severity of the low-severity disease, and $S_H > S_L$. Assuming that S_H and S_L are constant, $\Delta S = (S_H - S_L)\, \Delta$high%, and

$$\Delta LE = \beta_1 \Delta V + \beta_2 (S_H - S_L)\, \Delta \text{high\%}$$

The change in life expectancy is directly related to the change in drug vintage and inversely related to the change in the percent of patients with the high-severity disease.

Suppose that drugs for the low-severity disease (nervous system disorders) tend to be newer than drugs for the high-severity disease (cardiovascular disease), so that there is an inverse correlation across states between ΔV and Δhigh%: states with smaller increases in mean severity will have larger increases in drug vintage. In this case, failure to control for changes in severity (Δhigh%) will result in overestimation of the effect of drug vintage on life expectancy.

We will control for the incidence of one highly severe disease—AIDS—but unfortunately data on the incidence of other diseases, by state and year, are not available. Therefore direct measurement of mean disease severity (or the percent of patients with high-severity diseases) by state and year is not feasible. However, provided that the distribution of drugs utilized, by therapeutic class, is closely related to the distribution of patients, by disease, we can eliminate any potential bias in the vintage coefficient by using the following fixed-weighted index of drug vintage:

$$V'_{it} = \Sigma_c \, \text{class\%}_{ci.} \, V_{cit}$$

where V_{cit} = the mean vintage of prescriptions in therapeutic class c in state i in year t, and $\text{class\%}_{ci.}$ = the mean fraction of prescriptions in therapeutic class c in state i during the entire sample period, i.e. $\text{class\%}_{ci.} = (1 / T) \Sigma_t \, \text{class\%}_{cit}$, where $\text{class\%}_{cit}$ = the fraction of prescriptions in therapeutic class c in state i in year t.

Changes over time in the fixed-weighted index V' are entirely due to within-therapeutic class changes in drug vintage, not at all to between-class changes, i.e. shifts in the distribution of drugs by therapeutic class. In contrast, changes in the standard vintage index ($V_{it} = \Sigma_c \, \text{class\%}_{cit} \, V_{cit}$) are due to between- as well as within-class changes in vintage.

We will construct fixed-weighted indices of drug vintage using data from the Veterans Administration's National Drug File (U.S. Dept. of Veterans Affairs (2007)) on

the therapeutic class of each product. The VA drug classification is hierarchical, and has over 500 classes and subclasses. We will classify drugs at the highest level of the VA classification system, which has 32 classes. Table 1 shows data on the distribution and vintage of Medicaid prescriptions in 1991 and 2004, by major VA therapeutic class. In 2004, two classes of drugs (central nervous system medications and cardiovascular medications) accounted for half of Medicaid prescriptions. The share of Medicaid prescriptions that were central nervous system medications increased from 19% in 1991 to 29% in 2004. The mean vintage of central nervous system medications increased much more than the mean vintage of cardiovascular medications (16.5 years vs. 6.5 years). However for the nation as a whole, the fixed-weighted vintage index increased more during 1991-2004 than the standard index (11.4 years vs. 9.4 years).

We will estimate models using both the standard index and the fixed-weighted index of drug vintage. Performing this sensitivity analysis is useful, but eliminating the effects of shifts in the distribution of drugs by therapeutic class on vintage is not necessarily appropriate. If the rate of innovation varies across diseases/drug classes, states may benefit from innovation by changing the distribution of drugs consumed, by class, as well as by using newer drugs within drug classes.

Potential reasons for variation in the rate of increase of drug vintage

The rate of increase in drug vintage may vary across states due to both interstate differences in the types of diseases afflicting the population, and differences in the drugs used to treat given diseases. Suppose that

$$\Delta V_i = \Sigma_d \, share_{di} \, \Delta V_d$$

where

ΔV_i = the increase in the mean vintage of drugs in state i
$share_{di}$ = the fraction of state i's residents who have disease d
ΔV_d = the increase in the mean vintage of drugs to treat disease d

Even if the increase in the mean vintage of drugs to treat each disease is the same in every state, differences in the fractions of state residents who have various diseases ($share_{di}$) will result in interstate variation in the increase in the mean vintage of drugs.[4]

The relative incidence of various diseases does vary across states. This is illustrated by Figure 4, which plots the state-level incidence rate (cases per 100,000) of colon & rectum cancer against the incidence rate of prostate cancer for males in 2002. The correlation across states between these two incidence rates is not significantly different from zero (p-value = 0.61).

Moreover, due to medical practice variation, the increase in the mean vintage of drugs to treat any given disease is likely to vary across states. Medical practice variation is a well-documented phenomenon: there are 2514 citations for this term in the PubMed database. The Dartmouth Atlas of Health Care Project (Wennberg (2006)) has demonstrated "glaring variations in how health care is delivered across the United States."

Skinner and Staiger (2005) argue that medical practice variation may be partly due to variation in the frequency and likelihood of informational exchanges through networks or other social activities, which may in turn be related to both average educational attainment and other measures of social capital. They compared the adoption of several important innovations during the 20th century, ranging from advances at mid-century in hybrid corn and tractors, to medical innovations in the treatment of heart attacks at the end of the century. They found a very strong state-level correlation with regard to the adoption of new and effective technology, and this correlation held across a variety of industries and time periods. These results are suggestive of state-level factors associated with barriers to adoption. These barriers may be related to information or network flows, given that farmers, physicians, and individual computer users conduct their business in often small and isolated groups, and therefore are most vulnerable to potential information asymmetries.

Interstate differences in government health care policy also contribute to practice variation. In the last few years, some state Medicaid programs and private managed care

[4] Our econometric model will control (via state fixed effects) for the effects of permanent, or relatively stable, differences between states in the relative incidence of various diseases.

plans have restricted access to certain drugs, especially newer, more expensive drugs. One important type of restriction is a "prior authorization" requirement: a prescription will not be dispensed without prior authorization by program officials. Lichtenberg (2005d) examined the effect of access restrictions on the vintage of drugs used by Medicaid enrollees. The sample included 50 brand name drugs in six important therapeutic classes: antidepressants, antihypertensives, cholesterol-lowering drugs, diabetic drugs, osteoporosis/menopause drugs, and pain management medications. The extent of access restrictions varied considerably across states. Twelve states did not restrict any of the 50 drugs. Five states restricted over 47% of the drugs, and one—Vermont—restricted 43 of the 50 drugs. The vintage of Medicaid prescriptions increased more slowly in states that imposed more access restrictions.[5]

II. Econometric model

We will investigate the effects of drug vintage, behavioral risk factors, and other variables on life expectancy, productivity, and medical expenditure by estimating models of the following form:

$$Y_{it} = \beta X_{it} + \alpha_i + \delta_t + \varepsilon_{it} \qquad (1 = 1,\ldots,50;^{6}\ t = 1991,\ldots,2004) \qquad (1)$$

where Y is one of the following variables:

LE_{it} = life expectancy at birth in state i in year t
$LE65_{it}$ = life expectancy at age 65 in state i in year t
$productivity_{it}$ = the log of gross state product per employee in state i in year t
$expend_{it}$ = the log of per capita medical expenditure, total or by type of service, in state i in year t

and X includes all of the following variables:

$vint\_medicaid\_rx_{it}$ = the mean vintage of Medicaid prescriptions in state i in year t
$vint\_medicare\_rx_{it}$ = the mean vintage of Medicare drug treatments in state i in year t
$income_{it}$ = the log of per capita personal income in state i in year t
edu_{it} = an index of mean educational attainment of residents of state i in

[5] Lichtenberg (2006) presents a theoretical argument that the vintage of drugs is also likely to depend on the extent of prescription drug coverage, and empirical evidence that supports this argument.
[6] Arizona is excluded from the sample because it does not participate in the Medicaid Drug Rebate Program.

year t

$health\_cov_{it}$ = the % of residents covered by health insurance in state i in year t

bmi_gt25_{it} = the % of residents with BMI > 25 in state i in year t

now_smoke_{it} = the % of residents who are current smokers in state i in year t

$aids_{it-2}$ = the number of AIDS (Acquired Immune Deficiency Syndrome) cases reported per 100,000 population in state i in year t-2

α_i and δ_t represent state fixed effects and year fixed effects, respectively. Eq. (1) will be estimated by weighted least squares (WLS), weighting by pop_{it}, state i's population in year t.

In principle, there is some risk of feedback, or reverse causality, from life expectancy to some of the explanatory variables, especially mean income and education. Ceteris paribus, increases in life expectancy lead to an increase in the fraction of the population that is elderly. As shown in Figure 5, mean income and education of elderly people is significantly lower than that of non-elderly people. Hence unobserved shocks that increase a state's longevity could reduce its mean income and education, causing a downward bias in the coefficients of these variables. However, the share of the population that is elderly need not be increasing faster in states with larger increase in life expectancy; these states could have higher birth and/or net immigration rates.

In practice, the share of the population that is elderly *is* increasing faster in states with larger increase in life expectancy, but the relationship is not very strong. By using estimates of this relationship and the age profiles shown in Figure 5, we obtained estimates of the feedback effect of life expectancy on income and education, via population age structure. These calculations indicated that the downward biases in the income and education coefficients in the longevity equations would be extremely small.

III. Data sources and descriptive statistics

Life expectancy. The government does not publish data on life expectancy, by state, so we constructed estimates using data on the number of deaths by age group, year, and state of residence from the Multiple Cause-of-Death Mortality Data from the National Vital Statistics System of the National Center for Health Statistics.[7] Each record in the

[7] Murray et al (2006) also computed state and local estimates of life expectancy.

microdata is based on information abstracted from death certificates filed in vital statistics offices of each State and District of Columbia. The average number of records (deaths) per year is about 2.3 million. We also used population data from CDC Wonder Bridged-Race Population Estimates (Vintage 2004, http://wonder.cdc.gov/Bridged-Race-v2004.HTML).[8] As shown in Figure 6, the population-weighted means of my state estimates of LE are quite similar to the NCHS national estimates.

Productivity and per capita income. These data were obtained from two Bureau of Economic Analysis Regional Economic Accounts databases: the Gross Domestic Product by State database (http://www.bea.gov/regional/gsp/), and the State Annual Personal Income database (http://www.bea.gov/regional/spi/).

Per capita medical expenditure. The CMS Health Accounts by State database provides data on the following categories of health expenditure, by state and year (1980-2005): Total Health Care Expenditure, Hospital Care, Physician Services, Other Professional Services, Dental Services, Home Health Care, Prescription Drugs, Other Non-Durable Medical Products, Durable Medical Products, Nursing Home Care.

Vintage of Medicaid prescriptions. The mean vintage of Medicaid prescriptions is defined as follows:

$$\text{vint\_medicaid\_rx}_{it} = \frac{\Sigma_a \, \text{n\_medicaid\_ingred}_{ait} \, \text{vint}_a}{\Sigma_a \, \text{n\_medicaid\_ingred}_{ait}}$$

where

$\text{n\_medicaid\_ingred}_{ait}$ = the number of Medicaid prescriptions containing active ingredient a in state i in year t

vint_a = the vintage (year of initial FDA approval) of active ingredient a.

The first of these variables is constructed as follows:

$$\text{n\_medicaid\_ingred}_{ait} = \Sigma_p \, \text{n\_medicaid\_prod}_{pit} \, d_{pa}$$

where

$\text{n\_medicaid\_prod}_{pit}$ = the number of Medicaid prescriptions for product p in state i in year t

[8] We computed life expectancy using the following age classification: under 1 year, 1-4 years, 5-9 years, 10-14 years, 15-19 years, 20-24 years, 25-29 years, 30-34 years, 35-39 years, 40-44 years, 45-49 years, 50-54 years, 55-59 years, 60-64 years, 65-69 years, 70-74 years, 75-79 years, 80-84 years, 85 years and over.

d_{pa} = 1 if product p contains active ingredient a
= 0 if product p does not contain active ingredient a

$\Sigma_a d_{pa} = 1$ if product p is a single-ingredient product; $\Sigma_a d_{pa} > 1$ if it is a combination product. Data on $n\_medicaid\_prod_{pit}$ were obtained from CMS' Medicaid State Drug Utilization files (http://www.cms.hhs.gov/MedicaidDrugRebateProgram/SDUD/list.asp), which cover outpatient drugs paid for by State Medicaid agencies since the inception of the Medicaid Drug Rebate Program. Forty nine states (Arizona is excluded) and the District of Columbia cover drugs under the Medicaid Drug Rebate Program. The Medicaid data disclose the number of prescriptions, by product (NDC code), state, and year. There are currently over 37,000 products in the Medicaid Drug Product Data file (http://www.cms.hhs.gov/MedicaidDrugRebateProgram/09_DrugProdData.asp).

Data on d_{pa} were obtained from the ndc_denorm table in the Multum Lexicon database (http://www.multum.com/Lexicon.htm). There are currently over 2100 active ingredients in this database. Table 2 shows the top 25 active ingredients contained in 2004 Medicaid prescriptions, ranked by number of prescriptions.

Data on $vint_a$ were obtained from the Drugs@FDA database, produced by the FDA Center for Drug Evaluation and Research (http://www.fda.gov/cder/drugsatfda/datafiles/default.htm). This database includes several tables. The product table enumerates properties of the products included in each application, including their active ingredient(s). The supplements table provides the approval history for each application, including dates of approval. We define $vint_a$ as the earliest approval date of any product that contains active ingredient a.

Vintage of Medicare drug treatments. Medicare is a health insurance program for people age 65 or older, people under age 65 with certain disabilities, and people of all ages with End-Stage Renal Disease (permanent kidney failure requiring dialysis or a kidney transplant). All Medicare enrollees are covered by Medicare Part A (Hospital Insurance). Most Medicare enrollees elect to pay a monthly premium for Part B. Medicare Part B helps cover doctors' services and outpatient care. It also covers some other medical services that Part A doesn't cover, such as some of the services of physical and occupational therapists, and some home health care. Part B helps pay for these covered

services and supplies when they are medically necessary. In 2004, about 39 million Americans were enrolled in Medicare Part B.

Prior to January 1, 2006, when Medicare Part D was established, Medicare did not pay for most outpatient drugs, but the Medicare Part B (Medical Insurance) program did pay for drugs administered by health care providers, e.g. chemotherapy.

The Medicare drug vintage measure is similar to the Medicaid drug vintage measure, with one exception. For reasons discussed below, the Medicare index is expenditure-weighted, rather than quantity weighted:

$$\text{vint\_medicare\_rx}_{it} = \frac{\Sigma_a \text{ expend\_medicare\_ingred}_{ait} \text{ vint}_a}{\Sigma_a \text{ expend\_medicare\_ingred}_{ait}}$$

where

$\text{expend\_medicare\_ingred}_{ait}$ = expenditure on Medicare drug treatments containing active ingredient a in state i in year t

This variable is defined as follows:

$$\text{expend\_medicare\_ingred}_{ait} = \Sigma_d \text{ expend\_medicare\_drug}_{dit} \, e_{da}$$

where

$\text{expend\_medicare\_drug}_{dit}$ = expenditure on Medicare drug treatment d in state i in year t

e_{da} = 1 if Medicare drug treatment d contains active ingredient a
= 0 if Medicare drug treatment d does not contain active ingredient a

Data on $\text{expend\_medicare\_drug}_{dit}$ were obtained from annual Physician/Supplier Procedure Summary (PSPS) Master Files produced by CMS for each of the years 1991-2004. Each file is a 100% summary of all Part B Carrier and DMERC Claims processed through the Common Working File and stored in the National Claims History Repository. The files are large; the 2004 file has over 12 million records. The file enables us to compute total submitted services and charges, total allowed services and charges, total denied services and charges, and total payment amounts, by Medicare carrier and procedure. In most cases there is a one-to-one correspondence between a carrier and a state, so we can measure utilization and expenditure, by procedure and state.

As discussed in the technical documentation for the PSPS Master Files, Medicare carriers often make erroneous reports of service counts, but not of expenditures:

> Service counts for drugs should be reported using pricing units, e.g. J0120: Injection, Tetracycline up to 250 mg. In this example, 250 mg = 1 pricing unit or service. If the injection were for 500 mg then the pricing unit or service would be equal to 2, i.e. 500mg / 250mg = 2 pricing units or services. Many carriers are reporting the milligrams in the service count and MTUS Fields, e.g. 250 mg instead of 1 pricing unit. As a result the number of services are inflated, thereby deflating the average allowed charge.[9]

As shown in Figure 7, these reporting errors appear to cause spurious fluctuations in aggregate Medicare drug treatment service counts, but not in expenditures. Therefore, while we believe that a quantity-weighted vintage index is preferable to an expenditure-weighted index, due to errors in reporting service counts we will use an expenditure-weighted index of Medicare drug treatments.

Data on e_{da} were obtained from the ndc_denorm table in the Multum Lexicon database.

Table 3 shows the top 25 active ingredients contained in 2004 Medicare drug treatments, ranked by total services count. Comparison of Tables 2 and 3 indicates that the drugs administered by providers to Medicare beneficiaries are quite different from outpatient drugs used by Medicaid beneficiaries.

Demographic characteristics and behavioral risk factors. Data on body mass index (BMI), current smoking participation, health insurance coverage, and educational attainment were obtained from the Behavioral Risk Factor Surveillance System (BRFSS), which is the world's largest telephone survey. The BRFSS was established by the CDC in 1984, and was designed to collect state-level data. By 1994, all states, the District of Columbia, and three territories were participating in the BRFSS.

Data on the incidence of AIDS (the number of AIDS cases reported by state and local health departments) were obtained from the CDC's *AIDS Public Information Data Set* (http://www.cdc.gov/hiv/software/apids.htm). This data set contains counts of AIDS, by demographics; location (region and selected metropolitan areas); case-definition; month/year and quarter-year of diagnosis, report, and death (if applicable); and HIV exposure group (risk factors for AIDS). The data set covers the period 1981-2002. As

[9] Source: CMS, "2004 Limitations for the Physician/Supplier Procedure Summary Master File."

noted above, the measure of aids incidence we will include in our model of life expectancy will be the number of AIDS cases reported per 100,000 population lagged two years. Using this measure allows us to have the sample period end in 2004 rather than 2002. Also, Lichtenberg (2006) provides evidence that even before highly-active retroviral therapy was introduced in the mid-1990s, life expectancy of AIDS patients at time of diagnosis was 3.7 years, so overall life expectancy may depend on lagged AIDS incidence more than it depends on contemporaneous AIDS incidence.[10]

Table 4 shows population-weighted sample means of the variables included in eq. (1), by year. Table 5 shows sample means, by state. Figure 8 shows the increase in the fixed-weighted drug vintage index 1991-2004, by state

IV. Empirical results

Estimates of eq. (1) based on the standard index of Medicaid drug vintage are shown in Table 6. Estimates of eq. (1) based on the fixed-weighted index of Medicaid drug vintage are shown in Table 7. Overall, the two sets of estimates are fairly similar. We will discuss the estimates based on the fixed-weighted index, noting differences where appropriate.

The dependent variable in column 1 of Table 7 is life expectancy at birth. The coefficients on both Medicaid and Medicare drug vintage are positive and highly significant (p-value < .0001). This indicates that states in which the vintage of both self- and provider-administered drugs grew faster than average had above-average increases in life expectancy. The coefficients on the three behavioral risk factors (aids, bmi_gt25, and now_smoke) are all negative and significant. Life expectancy grew more slowly in states with larger increases (or slower declines) in AIDS, obesity, and smoking rates. The coefficients on educational attainment and health insurance coverage are not statistically significant. The coefficient on per capita income is *negative* and significant: states with high income growth had smaller longevity increases, *ceteris paribus*. This may be consistent with findings by Ruhm (2000, 2002, 2003, 2004, 2006, forthcoming).

[10] By 2001, life expectancy of AIDS patients at time of diagnosis is estimated to have increased to about 26 years.

The dependent variable in column 2 of Table 7 is life expectancy at age 65. The signs and significance of these coefficients are similar to those in column 1. Below we will use these coefficients to assess the contributions of medical innovation and changes in risk factors and income to longevity growth during the period 1991-2004. But first we will review the estimates of the productivity and medical expenditure regressions in Table 7.

The dependent variable in column 3 of Table 7 is real gross state product per employee. The coefficient on Medicaid drug vintage (but not on Medicare drug vintage) is positive and highly significant (p-value < .0001). States with larger increases in Medicaid drug vintage had faster productivity growth, conditional on income growth and the other factors in eq. (1). The increase in Medicaid drug vintage is estimated to have increased output per employee by about 1% per year. Much of this may be attributable to increased hours worked per employee. Based on a study of disease-level household survey data from the period 1982–1996, Lichtenberg (2005c) concluded that pharmaceutical innovation reduced the number of work-loss days per employed person by 1.0% per year.

Productivity growth is likely to depend on non-pharmaceutical as well as pharmaceutical innovations. Moreover, Skinner and Staiger (2005) found a very strong state-level correlation with regard to the adoption of new and effective technologies, and this correlation held across a variety of industries and time periods. Therefore, the coefficient on Medicaid drug vintage in the productivity regression may be overestimated, i.e. it may be capturing the productivity effect of other, unmeasured innovations.

Measuring the adoption of most innovations, by state and year, is not feasible, but there is one important innovation whose diffusion can be tracked: use of personal computers in the home. In six years during the period 1994-2003, respondents to the Current Population Survey indicated whether or not they used a computer at home. As shown in Figure 9, the percent of people using computers at home increased from 25% in 1994 to 62% in 2003. The rate of increase varied considerably across states.

We did not include the computer use measure in our basic model, because doing so would require a 57% reduction in sample size. However, we assessed the sensitivity

of our estimates to controlling for computer use. We found that changes in Medicaid drug vintage were uncorrelated across states with changes in computer use, both unconditionally, and controlling for income, education, and other factors. When computer use is included in the longevity and productivity equations, its coefficient is not significant in any equation. Controlling for computer use *increases* the Medicaid drug vintage coefficient in the productivity equation by 26%; it reduces the Medicaid drug vintage coefficient in the life expectancy at birth and at age 65 equations by 25% and 17%, respectively, but they remain highly significant. Thus at least one attempt to control for the adoption of non-medical innovations does not have a substantial impact on our estimates.

Now let's consider the estimates of the per capita medical expenditure equations. The coefficient on Medicaid drug vintage in the drug expenditure equation is .035 and is highly significant. This suggests that a one-year increase in Medicaid drug vintage causes drug expenditure to increase by 3.5%. This is quite consistent with Lichtenberg's (2006) estimate of the slope of the vintage-price profile based on cross-sectional micro data from the 2002 Medical Expenditure Panel Survey; he found that a one-year increase in vintage was associated with a 3.0% increase in the price of a prescription. Increases in educational attainment and the incidence of aids also increase drug expenditure. But states whose Medicare drug vintage is growing rapidly have lower growth in per capita drug expenditure.

The coefficients on the Medicaid drug vintage coefficient in the other expenditure equations (cols. 5-8) indicate that use of newer drugs is associated with increased utilization of home health care and nursing home care and lower expenditure on physicians. The coefficients on both the Medicaid and Medicare drug coefficients in the total expenditure equation (col. 9) are insignificantly different from zero. This indicates that states in which drug vintage has increased the most have not had above-average increases in overall medical expenditure. While use of newer drugs has increased some types of medical expenditure, it has reduced other types, and the expenditure reductions approximately offset the expenditure increases. This suggests that pharmaceutical-embodied technological change, like equipment-embodied technical change, is *non-*

neutral (Kopp and Smith (1985), Bartel and Lichtenberg (1987), Baltagi and Rich (2005)).

The other coefficients in column 9 suggest that increases in income, education, smoking, and the incidence of AIDS tend to increase per capita medical expenditure, and that expanded health insurance coverage reduces it.

V. Implications

Now we will use our estimates to assess the effects of the various factors on changes in U.S. life expectancy and on interstate differentials in life expectancy. The contribution of each factor to the 1991-2004 change in life expectancy is the coefficient of that factor in col. 1 or 2 of Table 7 times the 1991-2004 change in the mean of that factor in the last row of Table 4. As shown in the middle column of Table 8, life expectancy at birth increased by 2.33 years from 1991 to 2004. The estimates indicate that the growth in obesity and the growth in income both reduced the growth in life expectancy. If obesity and income had not increased, life expectancy at birth would have increased by 3.88 years. The increases in Medicaid and Medicare drug vintage account for 2.43 years (63%) of the "potential increase" in life expectancy. The declines in AIDS incidence and smoking account for 0.23 and 0.12 (6% and 3%) of the potential increase in life expectancy, respectively. About 1.1 years (28%) of the potential increase in life expectancy at birth is unexplained.[11]

As shown in the last column of Table 8, life expectancy at age 65 increased by 1.29 years from 1991 to 2004. If obesity and income had not increased, life expectancy at age 65 would have increased by 2.15 years. The increases in Medicaid and Medicare drug vintage account for 1.19 years (55%) of the potential increase in life expectancy at age 65. The declines in AIDS incidence and smoking account for 0.07 and 0.12 (3% and 5%) of the potential increase in life expectancy, respectively. About 0.8 years (36%) of the potential increase in life expectancy at age 65 is unexplained.

Although use of newer drugs does not appear to have increased *annual* medical expenditure, it probably has increased *lifetime* medical expenditure. The increase in the

[11] The unexplained component is reflected in the year fixed effects of eq. (1).

latter may be approximately equal to total medical expenditure during the 2.43 additional years of life attributable to increasing drug vintage. As shown in Figure 10, in 1996 mean medical expenditure of people age 75-84 was $6153—56% more than the mean medical expenditure of all Americans. This implies that the increase in lifetime medical cost per life-year gained from using newer drugs has been about $6153. Medical interventions that cost this amount are generally considered to be highly cost effective.

Differences in drug vintage explain some of the interstate variation in life expectancy, but the fraction of cross-sectional variance explained is smaller than the fraction of aggregate time-series variance (growth) explained. For example, as shown in **means_state**, the mean value of New Jersey's Medicaid fixed-weighted index of drug vintage is almost three years higher than the value of Tennessee's index. (These states used the newest and oldest drugs, respectively.) Our estimates imply that this difference would result in about a 6-month difference in life expectancy at birth. This is about 20% of the mean actual life expectancy differential (2.3 years) between the two states.

VI. Summary and conclusions

The rate of increase in longevity has varied considerably across states since 1991. This paper has examined the effect of medical innovation, behavioral risk factors (obesity, smoking, and AIDS incidence), and other variables (education, income, and health insurance coverage) on longevity using longitudinal state-level data. This approach controls for the effects of unobserved factors that vary across states but are relatively stable over time (e.g. climate and environmental quality), and unobserved factors that change over time but are invariant across states (e.g. changes in Federal government policies). We also analyzed interstate variation in productivity (output per employee) growth, and in the growth of per capita medical expenditure (total, and by type, e.g. expenditure on physicians, prescription drugs, and hospital care).

We found that states in which the vintage of both self- and provider-administered drugs grew faster than average had above-average increases in life expectancy, whether or not we adjusted for state-specific changes in the distribution of disease. However

since we were unable to control for the vintage of non-pharmaceutical medical services, and the latter may be correlated with drug vintage, the drug vintage coefficients we estimated may to some extent reflect the effect of other medical innovation as well as the effect of drug innovation.

Life expectancy grew more slowly in states with larger increases (or slower declines) in AIDS, obesity, and smoking rates. Consistent with a number of recent studies, states with high income growth had *smaller* longevity increases, ceteris paribus.

States with larger increases in Medicaid drug vintage had faster productivity growth, conditional on income growth and the other factors. The increase in Medicaid drug vintage is estimated to have increased output per employee by about 1% per year. Much of this may be attributable to increased hours worked per employee. In principle, the coefficient on Medicaid drug vintage in the productivity regression may be overestimated, i.e. it may be capturing the productivity effect of other, unmeasured innovations. But controlling for a potentially important non-medical innovation—computer use in the home—did not have a substantial impact on our estimates.

Increases in income, education, smoking, and the incidence of AIDS tend to increase per capita medical expenditure; expanded health insurance coverage reduces it. States in which drug vintage has increased the most have not had above-average increases in overall medical expenditure. While use of newer drugs has increased some types of medical expenditure, it has reduced other types, and the expenditure reductions approximately offset the expenditure increases. This suggests that pharmaceutical-embodied technological change, like equipment-embodied technical change, is non-neutral. Although use of newer drugs does not appear to have increased *annual* medical expenditure, it probably has increased *lifetime* medical expenditure. But the increase in lifetime medical cost per life-year gained from using newer drugs has been quite low.

The estimates indicate that the growth in obesity and the growth in income both reduced the growth in life expectancy. If obesity and income had not increased, life expectancy at birth would have increased by 3.88 years, not just 2.33 years. The increases in Medicaid and Medicare drug vintage account for 2.43 years (63%) of the "potential increase" in life expectancy. The declines in AIDS incidence and smoking account for 0.23 and 0.12 (6% and 3%) of the potential increase in life expectancy,

respectively. About 1.1 years (28%) of the potential increase in life expectancy at birth is unexplained. Differences in drug vintage explain some of the interstate variation in life expectancy, but the fraction of cross-sectional variance explained is smaller than the fraction of aggregate time-series variance (growth) explained.

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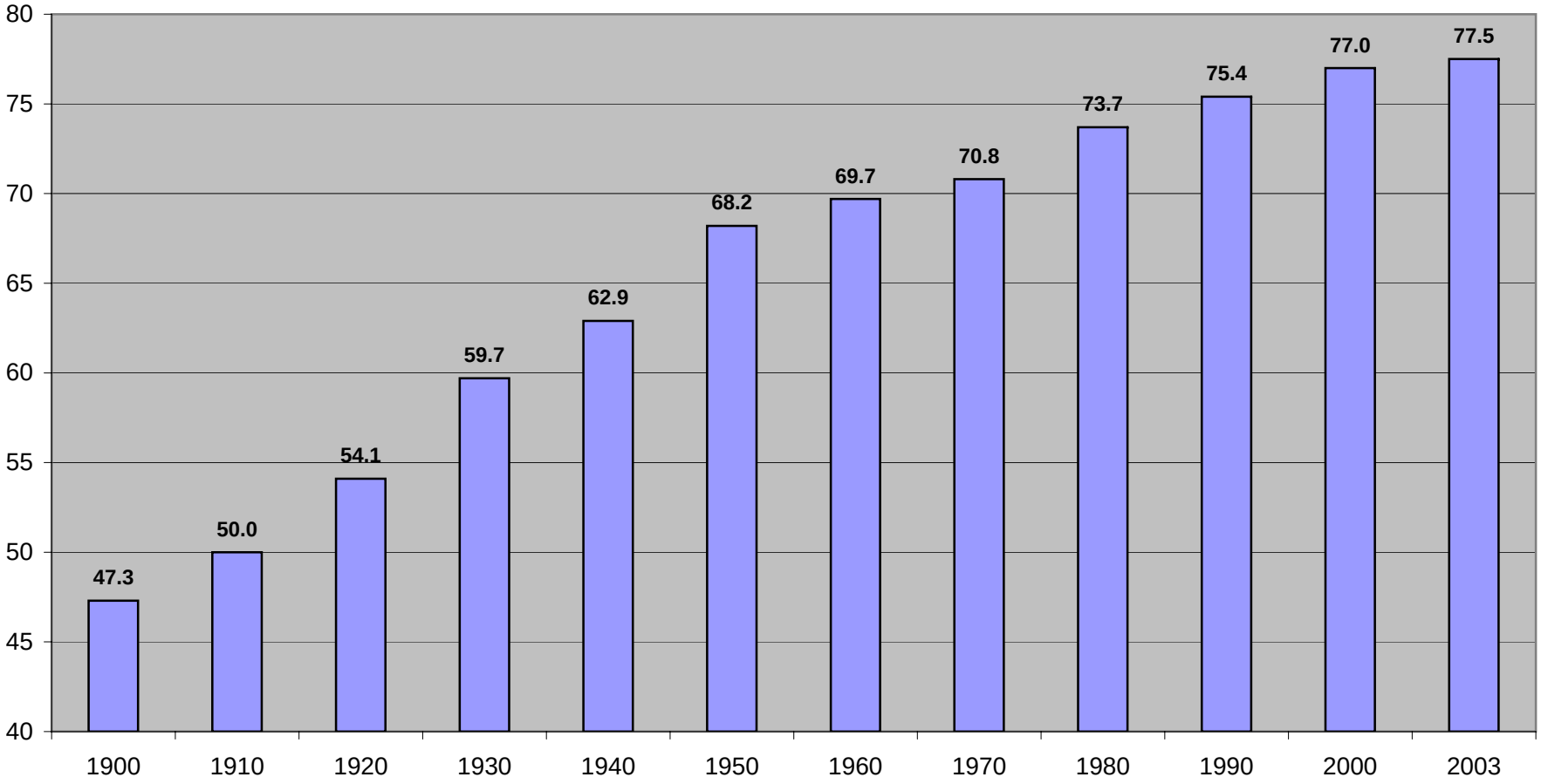
Figure 1
U.S. life expectancy at birth, 1900-2003



Arias E. United States life tables, 2003. National vital statistics reports; vol 54 no 14. Hyattsville, MD: National Center for Health Statistics. 2006. http://www.cdc.gov/nchs/data/nvsr/nvsr54/nvsr54_14.pdf
Table 12. Estimated life expectancy at birth in years, by race and sex: Death-registration States, 1900-28, and United States, 1929-2003

Figure 2
Increase in life expectancy at birth 1991-2004, by state

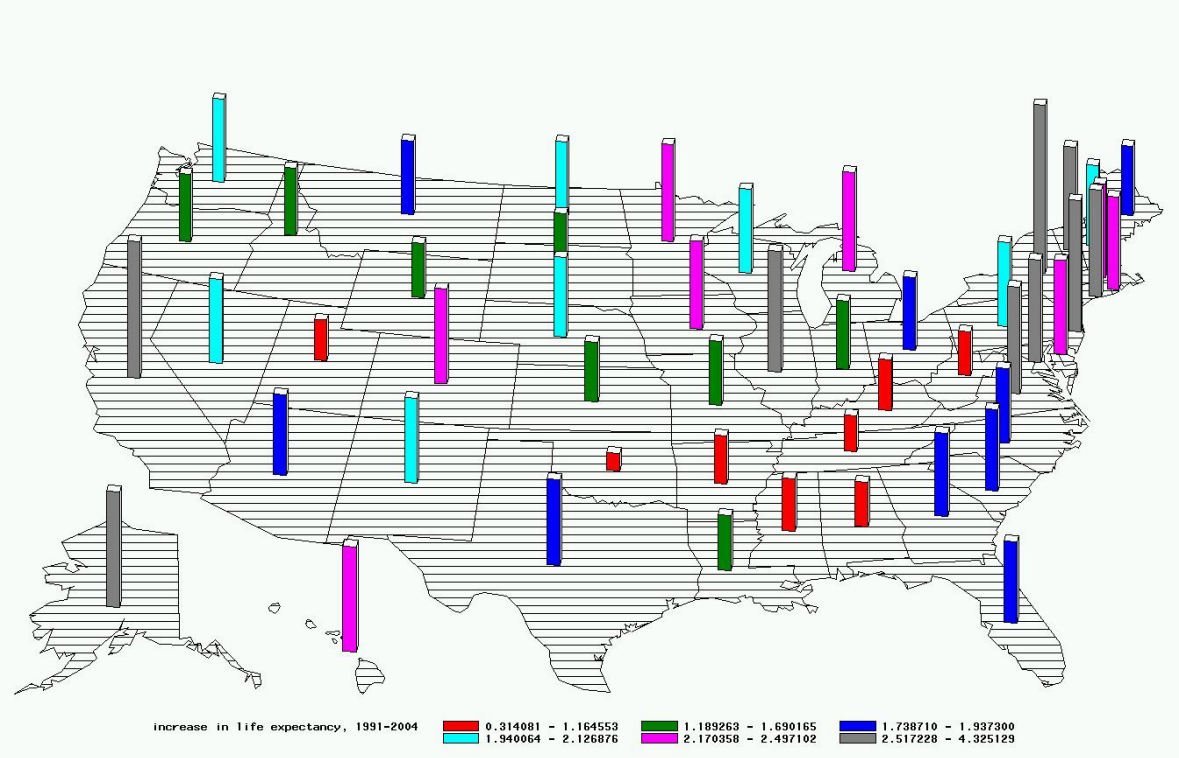
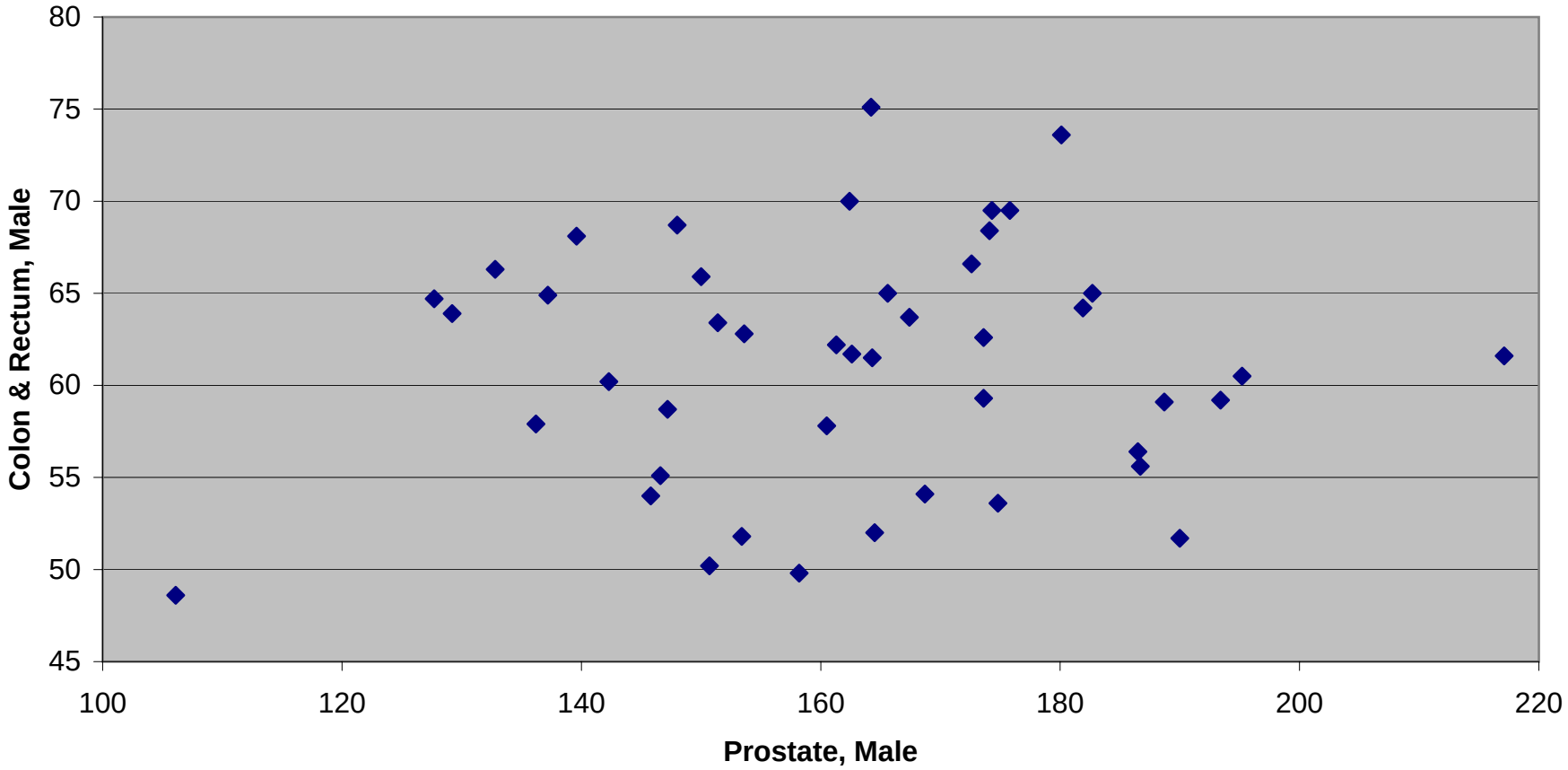


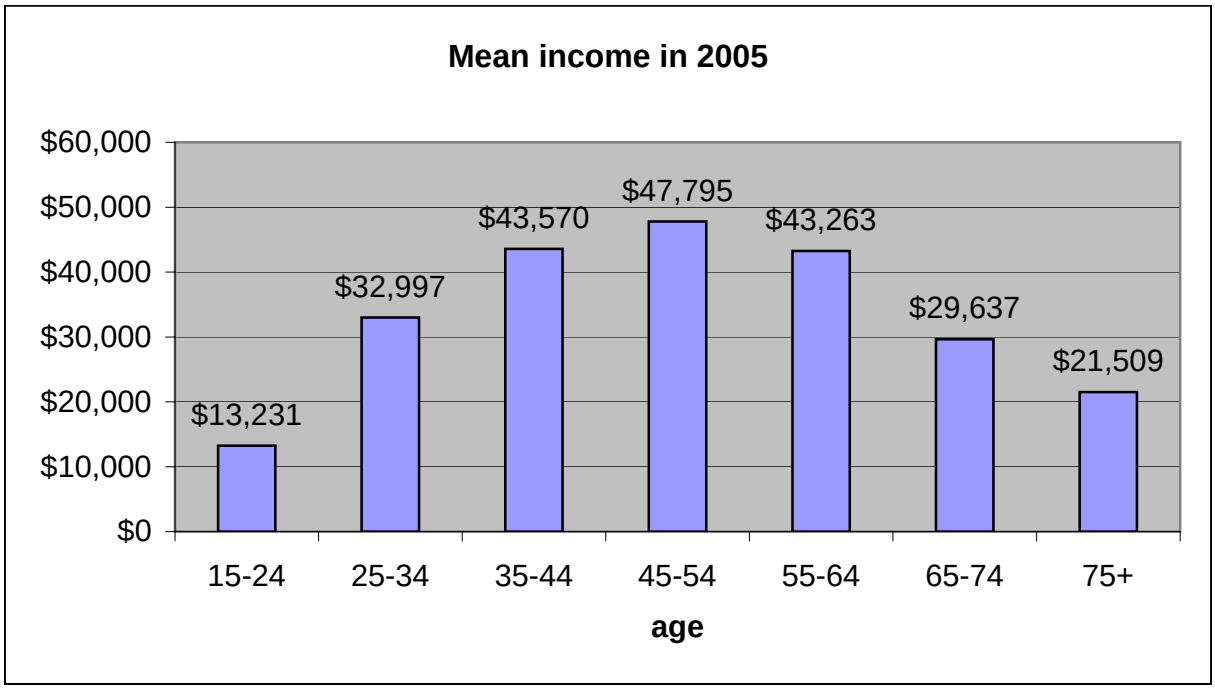
Figure 4
Annual incidence rates (cases per 100,000) of
prostate and colon & rectum cancer, males, 2002, by state



http://statecancerprofiles.cancer.gov/incidencerates/incidencerates.html

Figure 5

Age-income and age-education profiles



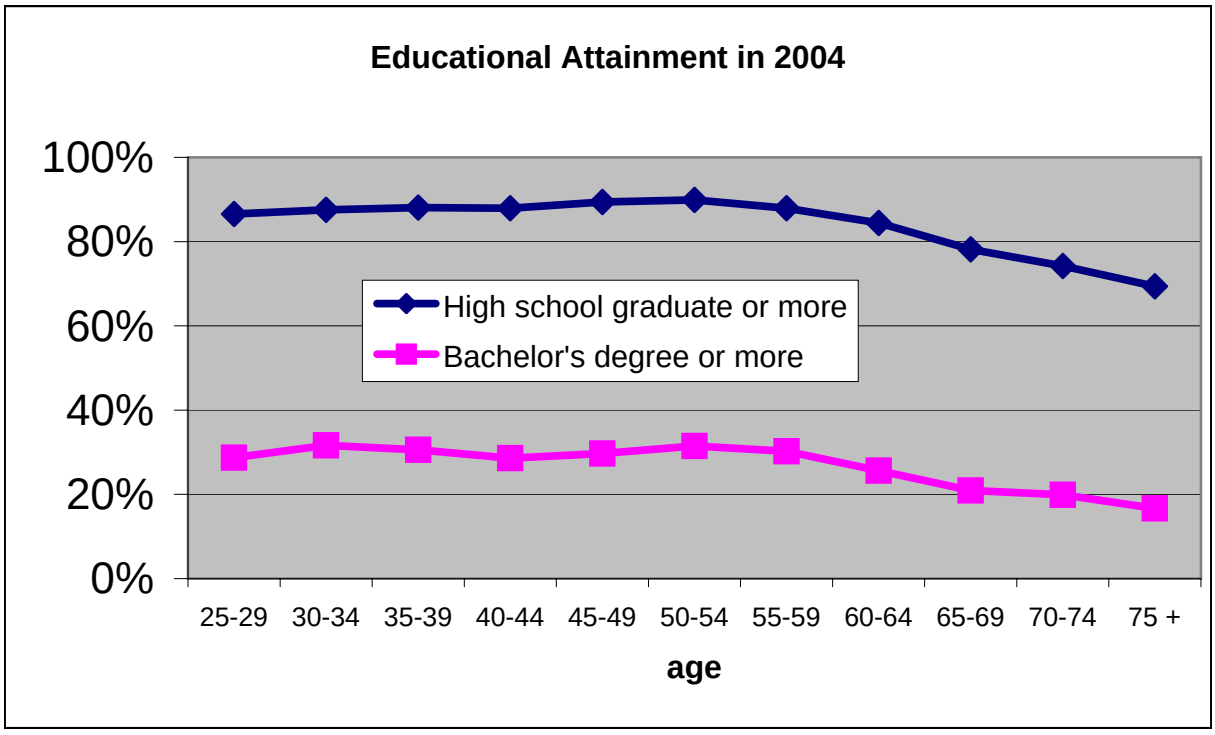


Figure 6
Comparison of population-weighted mean of
my state-level estimates of life expectancy at birth to NCHS national estimate

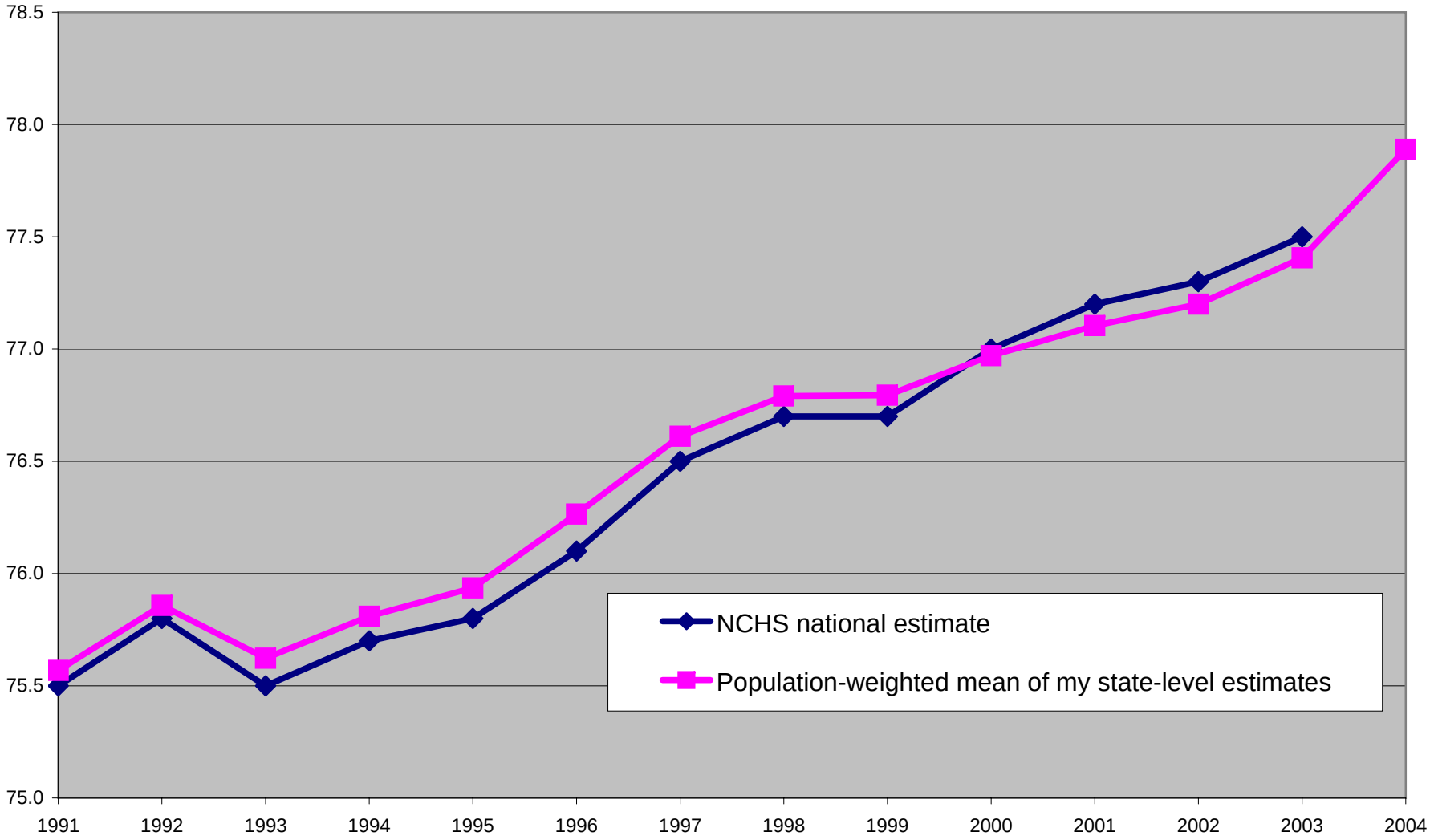


Figure 7
Reported aggregate Medicare drug treatment service counts and allowed charges, 1991-2004

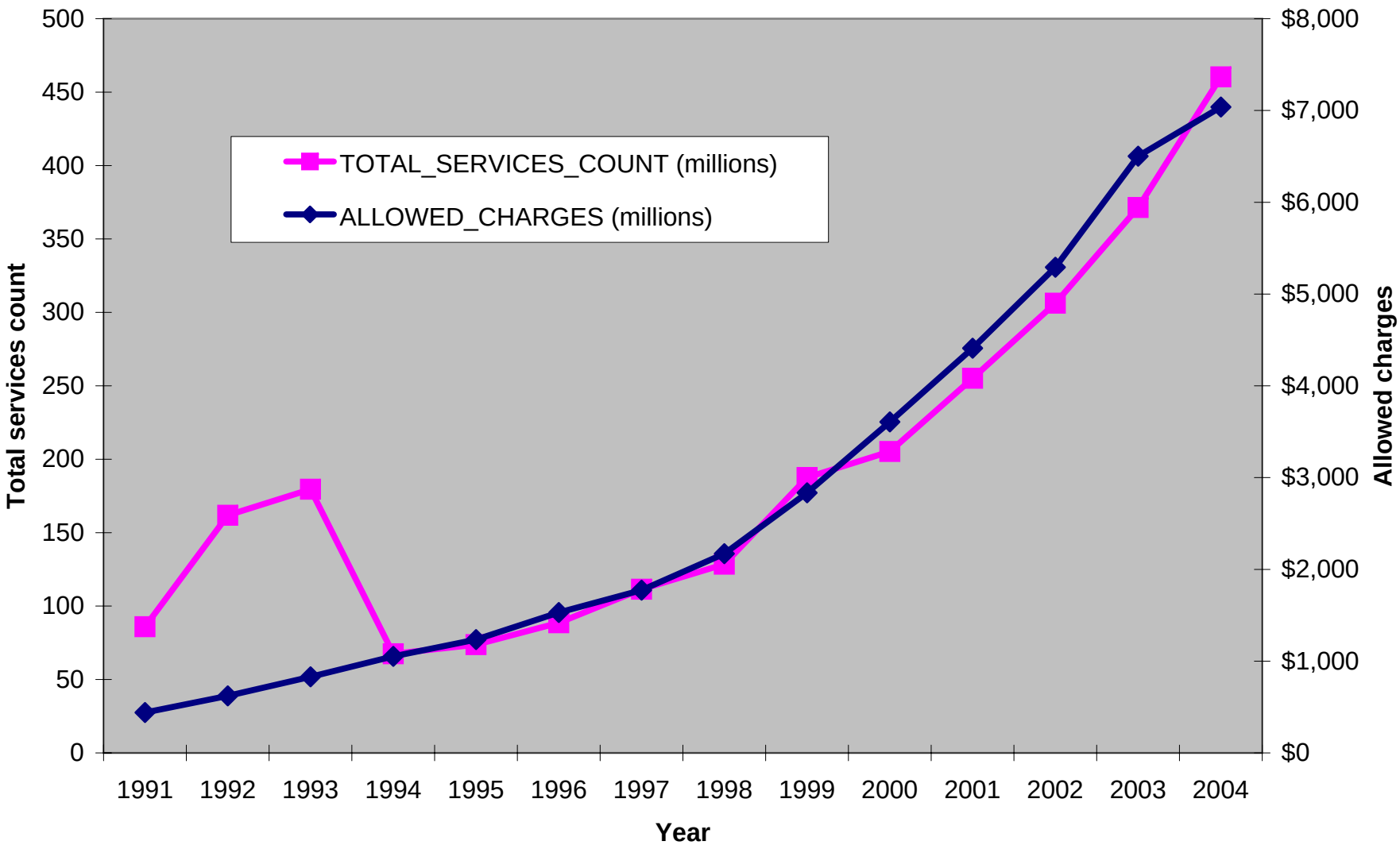


Figure 8
Increase in fixed-weighted drug vintage index 1991-2004, by state

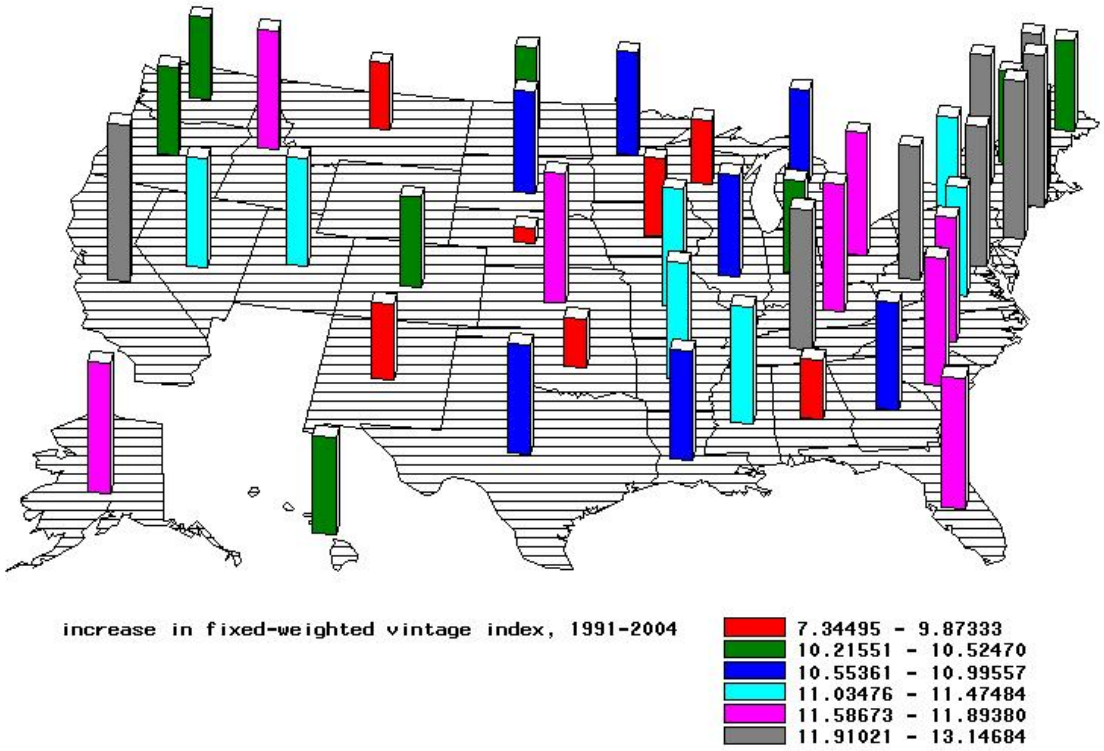


Figure 9
% of people using computer at home, 1994-2003

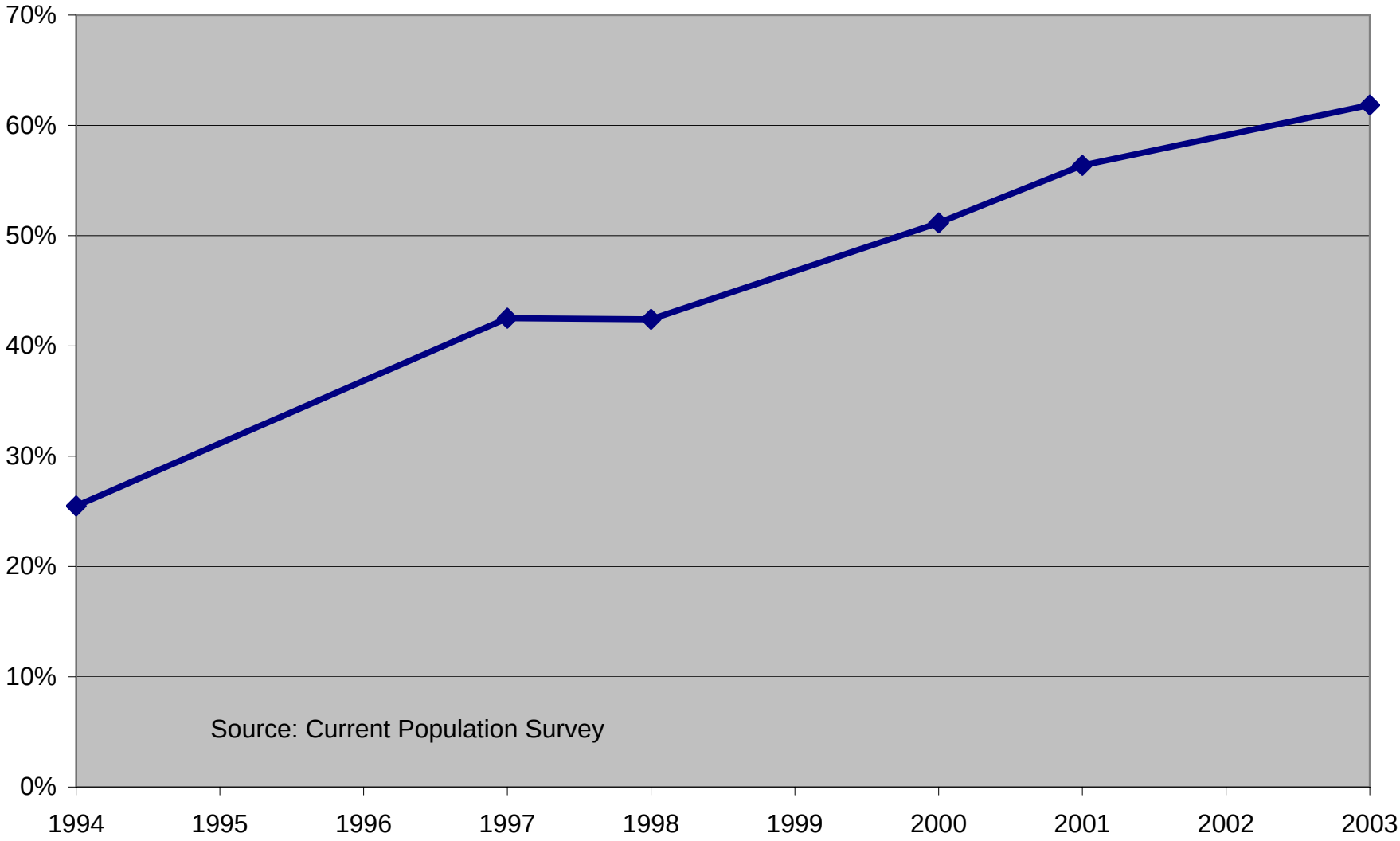
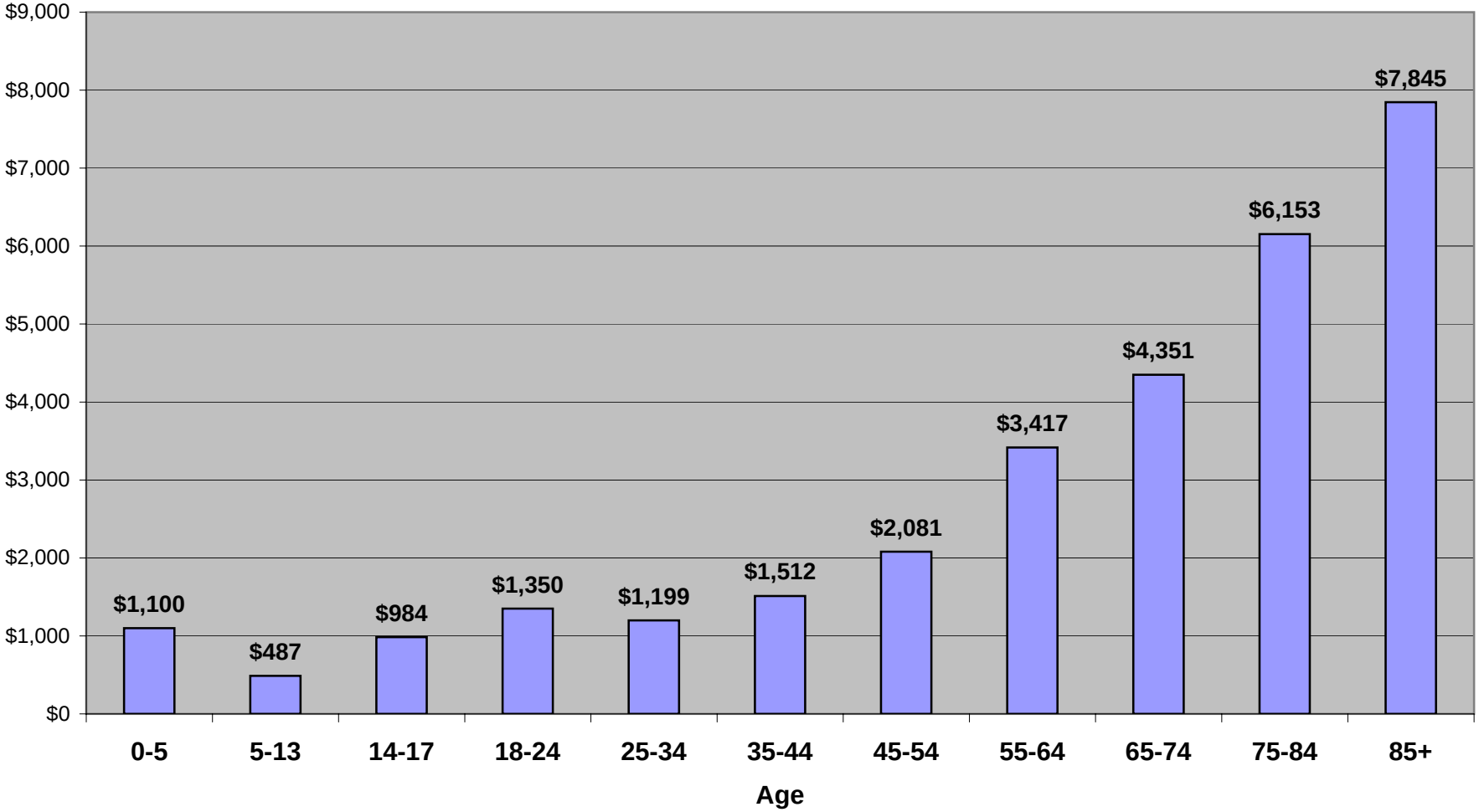


Figure 10
Mean medical expenditure per person in 1996, by age



Source: MEPS HC-011:1996 Full Year Use and Expenditure Data and MEPS HC-003, 1996 Panel Population Characteristics and Utilization Data for 1996

Table 1
Distribution and vintage of Medicaid prescriptions in 1991 and 2004, by major therapeutic class

Major therapeutic class	share of rx's		Mean vintage	
	1991	2004	1991	2004
central nervous system medications	19%	29%	1967.6	1984.1
cardiovascular medications	21%	21%	1975.6	1982.1
antimicrobials	16%	9%	1970.4	1982.2
hormones/synthetics/modifiers	7%	8%	1971.6	1978.2
gastrointestinal medications	5%	6%	1978.4	1993.8
respiratory tract medications	7%	6%	1976.6	1986.6
musculoskeletal medications	7%	4%	1975.6	1987.5
antihistamines	3%	3%	1953.7	1976.4
dermatological agents	5%	3%	1968.7	1972.8
blood products/modifiers/volume expanders	1%	2%	1956.3	1986.7
ophthalmic agents	2%	2%	1972.3	1988.6
nasal and throat agents,topical	1%	2%	1974.1	1984.7
autonomic medications	2%	1%	1961.0	1974.3
therapeutic nutrients/minerals/electrolytes	2%	1%	1971.2	1972.4
genitourinary medications	1%	1%	1977.4	1980.9
vitamins	0%	1%	1952.1	1962.3
antineoplastics	0%	0%	1969.8	1976.3
immunological agents	0%	0%	1976.0	1992.0
dental and oral agents,topical	0%	0%	1962.6	1972.3
antiparasitics	1%	0%	1976.2	1972.7
antidotes,deterrents and poison control	0%	0%	1967.5	1975.6
pharmaceutical aids/reagents	0%	0%	1972.1	1971.5
irrigation/dialysis solutions	0%	0%	1968.9	1969.2
otic agents	0%	0%	1958.8	1988.5
rectal,local	0%	0%	1959.1	1976.2
miscellaneous agents	0%	0%	1950.0	1993.9
diagnostic agents	0%	0%	1957.5	1957.1
prosthetics/supplies/devices	0%	0%	1985.0	1985.0

Note: therapeutic classes are ranked by share of Rx's in 2004.

Table 2

Top 25 active ingredients contained in 2004 Medicaid prescriptions, ranked by number of prescriptions

active_ingredient	number of prescriptions
acetaminophen	48,661,138
hydrochlorothiazide	35,027,596
risperidone	31,534,553
levothyroxine sodium	29,278,356
amoxicillin (as trihydrate)	26,065,616
hydrocodone bitartrate	25,832,307
clonazepam	16,976,543
ethinyl estradiol	16,452,694
clavulanate potassium	16,295,635
fluticasone propionate	15,435,753
clarithromycin	13,826,324
lisinopril	13,678,282
verapamil hydrochloride	13,241,735
amitriptyline hydrochloride	12,650,203
erythromycin ethylsuccinate	11,849,113
trandolapril	11,730,763
ranitidine hydrochloride	11,421,621
fluoxetine hydrochloride	11,394,072
metformin hydrochloride	11,328,717
furosemide	10,908,503
levofloxacin	10,834,964
ibuprofen	10,791,720
potassium chloride	10,568,663
divalproex sodium	10,313,345
paroxetine hydrochloride	9,947,294

Table 3

Top 25 active ingredients contained in 2004 Medicare drug treatments, ranked by total services count

active_ingredient	TOTAL_SERVICES_COUNT
sodium chloride	55,426,498
mycophenolate mofetil	47,917,499
tacrolimus	43,062,403
heparin	36,659,665
oxaliplatin	27,314,244
cyclosporine	21,892,673
dexamethasone sodium phosphate	19,764,089
botulinum toxin type A	14,661,255
prednisone	10,913,119
infliximab	9,943,030
imiglucerase	9,010,483
triamcinolone acetonide	7,856,756
alpha-1 proteinase inhibitor	6,631,202
dolasetron mesylate	6,215,073
dextrose	6,185,437
sirolimus	5,822,688
bacteriostats	5,507,020
granisetron hydrochloride	5,324,628
cyanocobalamin	5,247,190
ondansetron hydrochloride	5,223,916
Rh0 (d) immune globulin human	4,845,732
methylprednisolone acetate	4,543,014
iron sucrose	4,454,117
morphine sulfate	4,042,780
leucovorin calcium	3,787,017

Table 4

Population-weighted sample means, by year

Year	life expectancy at birth	life expectancy at age 65	log of gross state product per employee	log of per capita medical expenditure	log of per capita hospital expenditure	log of per capita physician expenditure	log of per capita drug expenditure	log of per capita home health expenditure	log of per capita nursing home expenditure	mean vintage of Medicaid prescriptions	mean vintage of Medicaid prescriptions (fixed-weighted)	mean vintage of Medicare drug treatments	log of per capita personal income	index of mean educational attainment	% of residents covered by health insurance	% of residents with BMI > 25	% of residents who are current smokers	number of AIDS cases reported per 100,000 population, year t-2
1991	75.6	17.5	10.82	7.87	6.99	6.52	5.16	3.95	5.37	1971.4	1971.2	1973.6	9.89	4.5	86%	44%	24%	16.6
1992	75.8	17.6	10.85	7.94	7.06	6.59	5.22	4.16	5.42	1971.7	1971.6	1975.2	9.94	4.6	86%	46%	23%	18.7
1993	75.6	17.4	10.85	7.99	7.09	6.63	5.26	4.34	5.45	1972.1	1972.2	1976.6	9.96	4.6	87%	47%	23%	22.9
1994	75.8	17.6	10.86	8.03	7.12	6.67	5.32	4.51	5.49	1972.6	1972.9	1980.1	10.00	4.5	87%	48%	22%	29.5
1995	76.0	17.6	10.87	8.08	7.15	6.70	5.42	4.65	5.57	1973.2	1973.6	1981.5	10.04	4.6	88%	49%	22%	29.5
1996	76.3	17.7	10.89	8.12	7.17	6.73	5.53	4.73	5.63	1974.1	1974.6	1982.8	10.09	4.6	87%	50%	23%	26.9
1997	76.6	17.8	10.92	8.16	7.19	6.77	5.64	4.76	5.67	1975.1	1975.9	1983.4	10.14	4.6	87%	51%	23%	25.2
1998	76.8	17.8	10.94	8.20	7.21	6.82	5.76	4.72	5.72	1976.1	1977.1	1985.0	10.20	4.7	87%	53%	23%	21.9
1999	76.8	17.7	10.96	8.25	7.25	6.87	5.92	4.66	5.72	1977.1	1978.4	1986.1	10.23	4.7	87%	54%	23%	17.4
2000	77.0	17.9	10.97	8.30	7.29	6.93	6.05	4.62	5.76	1978.2	1979.8	1987.2	10.30	4.7	87%	55%	22%	14.7
2001	77.1	18.0	10.97	8.37	7.36	7.00	6.18	4.66	5.81	1979.0	1980.7	1988.3	10.32	4.7	88%	57%	23%	13.7
2002	77.2	18.1	11.00	8.44	7.43	7.06	6.30	4.72	5.85	1979.7	1981.6	1989.3	10.33	4.7	87%	57%	22%	13.1
2003	77.4	18.3	11.02	8.51	7.49	7.14	6.38	4.81	5.88	1980.3	1982.4	1990.7	10.35	4.8	87%	58%	21%	12.1
2004	77.9	18.8	11.04	8.57	7.57	7.21	6.45	4.92	5.91	1980.7	1982.6	1992.2	10.40	4.8	87%	59%	20%	8.4
2004 - 1991	2.3	1.3	0.22	0.70	0.58	0.69	1.29	0.97	0.54	9.4	11.4	18.6	0.51	0.2	1%	15%	-4%	-8.3

Table 5

Sample means, by state (average values during 1991-2004)

State	life expectancy at birth	life expectancy at age 65	log of gross state product per employee	log of per capita medical expenditure	log of per capita hospital expenditure	log of per capita physician expenditure	log of per capita drug expenditure	log of per capita home health expenditure	log of per capita nursing home expenditure	mean vintage of Medicaid prescriptions	mean vintage of Medicaid prescriptions (fixed-weighted)	mean vintage of Medicare drug treatments	log of per capita personal income	index of mean educational attainment	% of residents covered by health insurance	% of residents with BMI > 25	% of residents who are current smokers	number of AIDS cases reported per 100,000 population, year t-2
Alabama	74.2	16.9	10.75	8.18	7.24	6.85	5.94	4.68	5.43	1974.7	1975.9	1984.5	9.98	4.4	85%	55%	23%	10.9
Alaska	76.5	17.9	11.18	8.27	7.44	6.92	5.54	2.85	4.47	1976.2	1977.4	1985.0	10.23	4.7	82%	57%	28%	5.3
Arkansas	74.8	17.2	10.68	8.08	7.16	6.64	5.76	4.47	5.65	1974.9	1976.3	1984.2	9.91	4.4	84%	54%	26%	8.6
California	77.7	18.5	11.02	8.14	7.10	7.01	5.50	4.37	5.19	1974.9	1975.8	1984.0	10.23	4.8	85%	50%	18%	23.0
Colorado	77.9	18.4	10.89	8.14	7.13	6.87	5.49	4.23	5.36	1976.3	1977.0	1984.5	10.25	4.9	87%	45%	22%	11.8
Connecticut	78.1	18.6	11.17	8.42	7.28	6.99	5.95	5.12	6.47	1977.3	1977.6	1984.1	10.47	4.9	91%	48%	21%	24.3
Delaware	76.1	17.6	11.33	8.32	7.33	6.93	5.99	4.73	5.81	1976.4	1977.2	1980.9	10.23	4.7	91%	54%	25%	26.8
District of Columbia	70.5	17.2	11.26	8.99	8.45	7.31	5.59	4.43	6.50	1976.3	1976.9	1983.3	10.50	4.9	89%	49%	19%	161.7
Florida	77.2	19.1	10.86	8.29	7.23	7.04	5.90	4.97	5.68	1977.1	1978.4	1982.2	10.14	4.6	84%	51%	23%	37.9
Georgia	74.9	17.0	10.94	8.15	7.20	6.86	5.81	4.56	5.28	1975.1	1976.7	1984.8	10.10	4.6	87%	55%	22%	21.5
Hawaii	79.8	20.3	10.91	8.20	7.28	6.90	5.64	3.80	5.11	1975.9	1976.3	1985.1	10.19	4.8	93%	45%	19%	13.7
Idaho	77.8	18.3	10.64	7.92	6.92	6.49	5.59	3.98	5.37	1976.0	1977.2	1984.2	9.98	4.7	85%	52%	20%	3.0
Illinois	76.2	17.6	11.00	8.20	7.30	6.78	5.76	4.38	5.77	1974.6	1975.8	1984.4	10.24	4.7	90%	53%	23%	14.8
Indiana	76.0	17.2	10.83	8.19	7.25	6.76	5.90	4.19	5.96	1975.7	1976.8	1984.0	10.08	4.6	89%	55%	26%	7.6
Iowa	78.2	18.4	10.72	8.15	7.24	6.60	5.75	4.35	6.05	1975.1	1976.0	1984.3	10.07	4.6	92%	55%	22%	3.3
Kansas	77.2	18.1	10.73	8.17	7.18	6.78	5.81	4.28	5.85	1976.2	1977.0	1983.7	10.11	4.8	90%	52%	22%	6.1
Kentucky	74.9	16.7	10.80	8.18	7.26	6.77	5.99	4.68	5.64	1974.9	1975.8	1983.4	9.97	4.2	85%	55%	29%	6.6
Louisiana	73.8	16.8	10.92	8.22	7.36	6.80	5.85	4.71	5.65	1975.8	1977.0	1984.0	9.96	4.5	79%	55%	24%	21.4
Maine	77.3	17.6	10.72	8.24	7.26	6.68	5.81	4.77	5.97	1976.5	1977.5	1984.4	10.04	4.6	88%	53%	23%	5.1
Maryland	76.0	17.6	10.96	8.23	7.23	6.92	5.87	4.30	5.75	1976.8	1977.2	1985.5	10.31	4.8	90%	52%	20%	32.2
Massachusetts	77.9	18.2	11.02	8.46	7.54	6.96	5.83	5.22	6.29	1976.4	1977.0	1985.0	10.37	4.9	91%	48%	22%	17.7
Michigan	76.2	17.5	10.98	8.16	7.26	6.67	5.89	4.53	5.51	1976.0	1977.0	1982.4	10.16	4.7	91%	56%	25%	8.4
Minnesota	78.8	18.7	10.87	8.30	7.21	7.04	5.71	4.52	6.07	1976.0	1976.6	1986.5	10.23	4.8	93%	54%	21%	5.3
Mississippi	73.4	16.7	10.67	8.05	7.22	6.53	5.82	4.71	5.48	1975.9	1977.3	1985.2	9.84	4.4	84%	57%	23%	12.8
Missouri	75.7	17.3	10.81	8.25	7.43	6.74	5.77	4.58	5.84	1976.0	1977.0	1983.9	10.09	4.5	88%	54%	26%	11.5
Montana	77.0	18.0	10.56	8.09	7.22	6.58	5.57	4.32	5.59	1975.6	1976.4	1984.5	9.95	4.7	84%	52%	22%	2.6
Nebraska	77.8	18.2	10.75	8.19	7.35	6.62	5.81	3.76	5.92	1975.9	1977.2	1985.3	10.11	4.6	91%	54%	21%	4.8

Table 5 (continued)

Sample means, by state (average values during 1991-2004)

State	life expectancy at birth	life expectancy at age 65	log of gross state product per employee	log of per capita medical expenditure	log of per capita hospital expenditure	log of per capita physician expenditure	log of per capita drug expenditure	log of per capita home health expenditure	log of per capita nursing home expenditure	mean vintage of Medicaid prescriptions	mean vintage of Medicaid prescriptions (fixed-weighted)	mean vintage of Medicare drug treatments	log of per capita personal income	index of mean educational attainment	% of residents covered by health insurance	% of residents with BMI > 25	% of residents who are current smokers	number of AIDS cases reported per 100,000 population, year t-2
Nevada	75.6	17.3	10.99	8.10	7.01	6.93	5.68	4.44	4.72	1976.6	1977.6	1986.1	10.23	4.7	84%	51%	27%	18.5
New Hampshire	78.1	18.0	10.84	8.21	7.19	6.84	5.75	4.64	5.77	1976.3	1977.0	1987.8	10.25	4.8	89%	50%	23%	5.0
New Jersey	77.0	17.9	11.17	8.29	7.24	6.92	5.97	4.77	5.90	1977.7	1978.6	1983.2	10.40	4.8	90%	49%	20%	33.4
New Mexico	76.9	18.6	10.78	7.99	7.13	6.49	5.40	4.50	5.00	1975.6	1976.6	1985.2	9.92	4.7	80%	50%	22%	8.5
New York	76.9	18.2	11.14	8.41	7.47	6.84	5.91	5.46	6.23	1977.1	1977.7	1983.1	10.32	4.7	88%	50%	23%	49.7
North Carolina	75.5	17.3	10.88	8.16	7.22	6.72	5.88	4.75	5.69	1976.2	1977.5	1984.2	10.08	4.5	87%	54%	24%	10.6
North Dakota	78.4	18.7	10.59	8.33	7.53	6.81	5.73	3.25	6.14	1975.8	1976.9	1985.0	10.00	4.6	89%	56%	22%	0.7
Ohio	76.1	17.2	10.88	8.25	7.30	6.79	5.82	4.55	6.08	1976.1	1977.1	1983.3	10.12	4.5	90%	54%	25%	7.2
Oklahoma	75.0	17.1	10.69	8.08	7.13	6.66	5.75	4.65	5.58	1976.1	1977.0	1985.5	9.98	4.5	84%	53%	24%	7.9
Oregon	77.4	18.0	10.78	8.11	7.03	6.83	5.51	3.83	5.39	1976.1	1976.2	1985.9	10.11	4.8	86%	52%	21%	10.4
Pennsylvania	76.5	17.6	10.92	8.35	7.43	6.86	5.99	4.52	6.09	1977.0	1977.8	1983.9	10.18	4.6	91%	54%	24%	14.7
Rhode Island	77.8	18.3	10.92	8.33	7.36	6.74	5.99	4.69	6.15	1977.0	1976.9	1981.0	10.17	4.7	91%	50%	23%	13.9
South Carolina	74.7	17.2	10.79	8.10	7.24	6.63	5.81	4.45	5.41	1976.4	1977.5	1983.9	9.98	4.5	86%	54%	24%	19.2
South Dakota	77.5	18.6	10.66	8.22	7.40	6.74	5.59	2.81	5.94	1976.3	1977.4	.	10.03	4.6	90%	55%	22%	1.6
Tennessee	74.7	16.9	10.82	8.30	7.34	7.00	6.09	4.75	5.67	1975.7	1975.6	1984.6	10.08	4.4	88%	53%	26%	10.9
Texas	76.3	17.7	10.94	8.13	7.19	6.82	5.64	4.80	5.33	1975.8	1977.8	1983.9	10.10	4.6	79%	54%	22%	18.7
Utah	78.5	18.7	10.77	7.94	6.98	6.52	5.58	4.19	5.00	1975.5	1976.7	1986.5	9.95	4.8	87%	49%	14%	6.7
Vermont	77.8	17.9	10.65	8.14	7.13	6.64	5.72	4.74	5.72	1976.2	1976.8	1988.7	10.09	4.8	89%	49%	21%	4.7
Virginia	76.5	17.4	10.95	8.09	7.14	6.73	5.78	4.18	5.48	1975.9	1976.8	1984.1	10.22	4.7	88%	52%	23%	14.0
Washington	77.9	18.3	10.98	8.16	7.10	6.84	5.67	4.40	5.59	1975.4	1976.1	1986.7	10.22	4.9	89%	51%	22%	11.5
West Virginia	74.7	16.5	10.75	8.22	7.35	6.75	6.02	4.55	5.63	1975.4	1976.7	1982.4	9.89	4.2	84%	56%	27%	4.6
Wisconsin	77.8	18.2	10.81	8.22	7.22	6.87	5.78	4.35	5.93	1975.9	1976.6	1984.0	10.13	4.6	91%	55%	24%	4.8
Wyoming	76.8	17.9	10.89	7.96	7.07	6.42	5.62	3.82	5.40	1975.7	1976.4	1984.3	10.12	4.7	84%	52%	23%	2.4

Table 6
WLS estimates of Equation 1 based on the standard index of Medicaid drug vintage

column	1	2	3	4	5	6	7	8	9
Dependent variable	life expectancy		producti	per capita medical expenditure					
	at birth	at age 65	vity	drug	HH	NH	hospital	physician	total
vint_medicaid_rx	0.211	0.143	0.009	0.028	0.103	0.013	0.003	-0.036	-0.003
tValue	9.44	12.06	4.07	7.14	7.96	2.64	0.92	-8.21	-1.15
Probt	<.0001	<.0001	<.0001	<.0001	<.0001	0.008	0.359	<.0001	0.253
vint_medicare_rx	0.038	0.014	0.001	-0.002	0.003	0.005	-0.003	-0.002	-0.001
tValue	5.93	4.00	1.18	-1.86	0.92	3.94	-3.26	-1.35	-1.60
Probt	<.0001	<.0001	0.240	0.064	0.360	<.0001	0.001	0.178	0.109
aids	-0.026	-0.007	-0.001	0.001	-0.002	0.000	0.002	0.003	0.002
tValue	-13.43	-7.15	-4.52	2.31	-1.62	0.47	6.61	6.80	8.92
Probt	<.0001	<.0001	<.0001	0.021	0.105	0.639	<.0001	<.0001	<.0001
bmi_gt25	-3.678	-1.765	0.004	0.250	-0.275	0.564	-0.073	0.024	0.078
tValue	-4.34	-3.92	0.05	1.69	-0.56	3.10	-0.61	0.15	0.83
Probt	<.0001	<.0001	0.958	0.091	0.574	0.002	0.545	0.884	0.407
now_smoke	-2.149	-2.296	-0.153	0.404	-0.019	0.926	0.143	0.058	0.272
tValue	-2.21	-4.45	-1.67	2.38	-0.03	4.44	1.03	0.30	2.53
Probt	0.027	<.0001	0.095	0.018	0.973	<.0001	0.305	0.763	0.012
edu	0.026	-0.018	-0.007	0.172	-0.255	0.072	0.057	0.154	0.107
tValue	0.16	-0.20	-0.47	5.84	-2.62	2.00	2.37	4.65	5.72
Probt	0.875	0.838	0.640	<.0001	0.009	0.046	0.018	<.0001	<.0001
health_cov	0.461	-0.276	0.145	-0.241	1.832	0.613	-0.254	-1.019	-0.420
tValue	0.52	-0.59	1.75	-1.56	3.58	3.23	-2.01	-5.87	-4.30
Probt	0.602	0.556	0.081	0.119	0.000	0.001	0.045	<.0001	<.0001
income	-1.346	-0.701	0.690	-0.017	0.856	-0.670	0.499	0.476	0.290
tValue	-2.22	-2.18	12.07	-0.16	2.44	-5.15	5.76	4.00	4.32
Probt	0.027	0.030	<.0001	0.874	0.015	<.0001	<.0001	<.0001	<.0001
RSquare	0.972	0.97295	0.9765	0.99217	0.91357	0.98451	0.975	0.964504	0.98772
CV	781.641	1780.844	516.82	1807.29	7523.84	2267.78	1181.1	1717.842	806.552
RootMSE	598.656	318.0922	56.494	104.506	346.476	128.588	85.634	117.5757	66.2665
DepMean	76.5896	17.86188	10.931	5.78244	4.60504	5.67023	7.2504	6.84438	8.21602

Table 7
WLS estimates of Equation 1 based on the fixed-weighted index of Medicaid drug vintage

column	1	2	3	4	5	6	7	8	9
Dependent variable	life expectancy		producti	per capita medical expenditure					
	at birth	at age 65	vity	drug	HH	NH	hospital	physician	total
vint_medicaid_rx	0.158	0.086	0.011	0.035	0.090	0.020	0.001	-0.040	-0.004
tValue	6.39	6.28	4.98	8.64	6.43	3.85	0.27	-8.69	-1.53
Probt	<.0001	<.0001	<.0001	<.0001	<.0001	0.0001	0.7867	<.0001	0.1264
vint_medicare_rx	0.034	0.011	0.000	-0.003	0.001	0.005	-0.003	-0.001	-0.001
tValue	5.09	3.02	0.79	-2.64	0.38	3.61	-3.33	-0.65	-1.53
Probt	<.0001	0.0027	0.4321	0.0085	0.7038	0.0003	0.0009	0.5142	0.1264
aids	-0.027	-0.009	-0.001	0.001	-0.002	0.000	0.002	0.002	0.002
tValue	-13.47	-7.90	-4.06	2.98	-1.80	0.94	6.32	6.37	8.64
Probt	<.0001	<.0001	<.0001	0.003	0.0728	0.3461	<.0001	<.0001	<.0001
bmi_gt25	-4.659	-2.408	-0.042	0.107	-0.789	0.493	-0.082	0.208	0.095
tValue	-5.31	-4.96	-0.53	0.74	-1.59	2.73	-0.68	1.26	1.02
Probt	<.0001	<.0001	0.5933	0.459	0.113	0.0064	0.4954	0.2065	0.3099
now_smoke	-3.182	-3.021	-0.191	0.283	-0.515	0.873	0.128	0.220	0.284
tValue	-3.18	-5.45	-2.11	1.71	-0.91	4.24	0.93	1.17	2.67
Probt	0.0016	<.0001	0.0351	0.0876	0.364	<.0001	0.3545	0.2426	0.0079
edu	0.029	0.001	-0.011	0.159	-0.264	0.064	0.058	0.164	0.108
tValue	0.16	0.01	-0.72	5.51	-2.66	1.76	2.39	4.98	5.77
Probt	0.87	0.995	0.4748	<.0001	0.0081	0.0787	0.0171	<.0001	<.0001
health_cov	1.455	0.595	0.141	-0.246	2.190	0.574	-0.227	-1.064	-0.416
tValue	1.60	1.18	1.72	-1.64	4.26	3.07	-1.81	-6.24	-4.31
Probt	0.1094	0.2366	0.0857	0.1011	<.0001	0.0022	0.0705	<.0001	<.0001
income	-1.679	-0.965	0.687	-0.040	0.749	-0.675	0.488	0.505	0.288
tValue	-2.67	-2.77	12.08	-0.39	2.10	-5.21	5.62	4.27	4.29
Probt	0.0079	0.0058	<.0001	0.6975	0.0362	<.0001	<.0001	<.0001	<.0001
RSquare	0.96985	0.968363	0.9767	0.99246	0.91082	0.98472	0.97494	0.965	0.98774
CV	812.738	1929.701	514.4	1776.4	7660.85	2257.36	1183.58	1708.87	806.875
RootMSE	622.464	344.6677	56.228	102.709	352.787	127.99	85.8109	116.958	66.2905
DepMean	76.5885	17.86119	10.931	5.78187	4.60507	5.66991	7.25014	6.84415	8.21571

Table 8

Estimated effects of various factors on changes in U.S. life expectancy

	Life expectancy (LE)	
	at birth	at age 65
Observed increase in LE	2.33	1.29
Contribution of factors reducing LE		
bmi_gt25	-0.70	-0.36
income	-0.86	-0.49
Total	-1.56	-0.85
Potential increase in LE	3.88	2.15
Contribution of factors increasing LE		
vint_medicaid_rx	1.80	0.98
vint_medicare_rx	0.63	0.21
aids	0.23	0.07
now_smoke	0.12	0.12
Total	2.78	1.38
Unexplained potential increase in LE	1.10	0.77

Appendix A

Correlation across states between changes in the vintage of Medicaid and non-Medicaid prescriptions

This appendix describes a test of the hypothesis that the extent of utilization of new drugs in the Medicaid program is strongly correlated with the extent of utilization of new drugs in general. We had access to data from a private company, NDCHealth, on the number of prescriptions, by NDC code, state (and five U.S. territories), month (January 2001-December 2003), and payer (Medicaid, other third party, and cash), for six important therapeutic classes of drugs: antidepressants, antihypertensives, cholesterol-lowering drugs, diabetic drugs, osteoporosis/menopause drugs, and pain management medications. Here are some summary statistics:

	N	mean	std dev.	min	max
	FDA approval year				
Medicaid	252,469,702	1986.44	1.51474	1961.22	2002
Other	2,244,589,497	1986.59	1.19334	1980.47	1999
Total	2,497,059,199	1986.58	1.18352	1980.85	1999
	share of Rx's for drugs approved after 1980				
Medicaid	252,469,702	0.81739	0.04221	0	1
Other	2,244,589,497	0.80292	0.02936	0.5	1
Total	2,497,059,199	0.80438	0.0297	0.5	1

These data were used to estimate the following equation:[12]

$$Y_{it} = \pi \, VINT\_MEDICAID_{it} + \alpha_i + \delta_t + \varepsilon_{it} \qquad (2)$$

where

$VINT\_MEDICAID_{it}$	= the mean vintage (FDA approval year) of Medicaid rx's in state i in month t
Y_{it}	= the mean vintage of all rx's *or* of non-Medicaid (third-party and cash) rx's in state i in month t
α_i	= a fixed effect for state i
δ_t	= a fixed effect for year t
ε_{it}	= a disturbance

[12] This equation was estimated by weighted least-squares, weighting by the total number of rx's, or the number of non-Medicaid rx's, in state i in month t.

Two alternative measures of vintage were used: the mean FDA approval year, and the share of prescriptions containing active ingredients approved after 1980. Estimates of eq. (1) are shown in Table 1. In all four equations, the estimate of π is positive and highly statistically significant (p-value <.0001). This indicates that the extent of utilization of new drugs in the Medicaid program is strongly correlated with the extent of utilization of new drugs in general. The vintage of non-Medicaid (and all) rx's tended to increase more in states with larger increases in the vintage of Medicaid rx's.

Appendix Table 1
The relationship between the vintage of Medicaid rx's and the vintage of other (or all) rx's

Model	1a	1b	2a	2b
Dependent Variable	mean FDA approval year of all rx's	share of all rx's containing active ingredients approved after 1980	mean FDA approval year of third-party & cash rx's	share of third-party & cash rx's containing active ingredients approved after 1980
Regressor	mean FDA approval year of Medicaid rx's	share of rx's containing active ingredients approved after 1980	mean FDA approval year of Medicaid rx's	share of Medicaid rx's containing active ingredients approved after 1980
Weight	total number of rx's	total number of rx's	number of third-party + cash rx's	number of third-party + cash rx's
π	0.291	0.316	0.237	0.253
std. err.	0.012	0.013	0.013	0.014
t-stat	25.19	23.98	18.98	17.75
p-value	<.0001	<.0001	<.0001	<.0001