Has pharmaceutical innovation reduced Social Security Disability growth?

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Abstract

This paper analyzes longitudinal state-level data during the period 1995-2004 to investigate whether use of newer prescription drugs has reduced the ratio of the number of workers receiving Social Security Disability Insurance benefits to the working-age population (the "DI recipiency rate").

All of the estimates indicate that there is a significant inverse relationship between disability recipiency and a good indicator of pharmaceutical innovation use: the mean vintage (FDA approval year) of Medicaid prescriptions. (Changes in Medicaid drug vintage are strongly correlated across states with changes in non-Medicaid drug vintage.) Disability recipiency is also consistently inversely related to the average wage rate and the fraction of state residents with at least a college education, and directly related to mean age.

From 1995 to 2004, the actual disability rate increased 30%, from 2.62% to 3.42%. The estimates imply that in the absence of any post-1995 increase in drug vintage, the increase in the disability rate would have been 30% larger: the disability rate would have increased 39%, from 2.62% to 3.65%. This means that in the absence of any post-1995 increase in drug vintage, about 418,000 more working-age Americans would have been DI recipients.

1. Introduction

A number of scholars have argued that medical innovation has played a major role in the long-term decline in disability. Based on an analysis of data from the Union Army pension program, Costa (2000) found that functional disability (difficulty in walking, difficulty in bending, paralysis, blindness in at least one eye, and deafness in at least one ear) in the United States has fallen at an average annual rate of 0.6 percent among men age 50 to 74 from the early twentieth century to the early 1990s, and that 24 to 41 percent of this decline was attributable to innovations in medical care. Manton et al (2006) found that the prevalence of chronic disability among elderly Americans declined from 1982 to 2004, and hypothesized that reductions in the incidence and severity of disease through biomedical interventions played an important role in this.

Pharmaceutical innovation is one type of medical innovation that may have significantly reduced disability, and may continue to do so in the future. Goldman et al (2005) predicted that the development of a neuroprotective drug could potentially reduce disability from stroke by 50%. Shekelle et al (2005) predicted that treating acute stroke with drugs that minimize cell death could result in a median decrease in disability of 30%, and that treatment with stem cell transplants could result in a median decrease in disability of 25%. The use of new pharmaceuticals may reduce disability in part because they embody fundamental research advances supported by the National Institutes of Health (NIH). Lichtenberg and Sampat (2011) found that 1/3 of all new drugs approved, and 58% of the priority-review new molecular entities approved, by the FDA during the period 1982-2006 had patents that cited NIH-supported publications or patents.

Two previous studies have investigated whether, in general, the introduction and use of newer prescription drugs reduces disability. One study (Lichtenberg (2005)) examined longitudinal data on a set of major chronic diseases during the period 1982-1996. It found that the larger the percentage increase in the cumulative number of drugs previously approved to treat a condition, the smaller the increase in the fraction of non-elderly adults with the condition who were unable to work, *ceteris paribus*. The other study (Lichtenberg and Virabhak (2007)) examined cross-sectional individual-level data

on a large sample of Americans surveyed in 1997. It found that people who used newer drugs had better post-treatment health than people using older drugs for the same condition, controlling for pre-treatment health, age, sex, race, marital status, education, income, and insurance coverage: they experienced fewer activity, social, and physical limitations, their perceived health status was higher, and they were more likely to survive. The disability measures used in both of these studies were self-reported measures derived from household surveys (the National Health Interview Survey and the Medical Expenditure Panel Survey).[1]

In this paper, we reexamine the question of whether use of newer prescription drugs reduces disability, using longitudinal state-level data during the period 1995-2004.[2] The disability measure we analyze is the ratio of the number of workers receiving Social Security Disability Insurance (DI) benefits to the working-age population.[3] As described by Autor and Duggan (2003), the federal government provides cash and medical benefits to individuals with disabilities through two programs: Social Security Disability Insurance and Supplemental Security Income (SSI). The medical eligibility criteria for the two programs are identical, requiring that an individual have a medically determinable impairment that prevents him or her from engaging in "substantial gainful work." SSI benefits are means-tested and do not require any prior work history, while DI benefits are an increasing function of prior earnings and are not means-tested. To apply for benefits, an individual must submit detailed medical, income, and asset information to a federal Social Security Administration (SSA) office, which makes the disability determination.

The DI recipiency rate started to grow rapidly in the early 1980s, and continued to grow during the period we will study: between 1995 and 2004, it increased by 30%, from 2.6% to 3.4%. Autor and Duggan developed a theoretical model to try to explain the rise

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[1] Benitez-Silva et al (2000) tested and were unable to reject the hypothesis that self-reported disability is similar to the information used by the Social Security Administration in making its award decisions. Their results indicate that disability applicants do not exaggerate their disability status at least in anonymous surveys such as the Health and Retirement Survey. Labriola and Lund (2007) found that information on self-reported days of sickness absence can be used to effectively identify "at risk" groups for disability pension.

[2] Previous studies have used longitudinal, regional-level (state-or country-level) data to examine the impact of medical innovation and other factors on longevity and hospitalization rates; see Lichtenberg (2006a, 2009, 2010).

[3] We will refer to this ratio as the DI recipiency rate.

in disability recipiency. According to their model, the probability that a person receives DI benefits depends on three key variables: his or her health status, the generosity of the disability program,[4] and labor market conditions. They tested some of the implications of their theory by estimating equations using longitudinal state-level data during the period 1978-1998. These equations included indicators of program generosity and labor market conditions. They found that the combined effect of increasing program generosity and worsening labor market conditions facing low-skill workers explained most of the rise in the DI recipiency rate.

Although their theoretical model implies that disability recipiency depends on health status, their empirical models did not include any measures of health or its determinants. Their justification for not controlling for these variables directly was that "conditional on age and education average wage and health changes are likely to be common across states." However, we think that there are good reasons to doubt this claim. As discussed in Lichtenberg (2010), even if the distribution of disease incidence across states were stable over time, different rates of medical innovation for different diseases would result in interstate variation in health changes. Moreover, the growth or decline in incidence of various diseases, such as HIV/AIDS, varies considerably across states. The growth in life expectancy (which is "age-adjusted") has also varied considerably across states; little if any of that variation is accounted for by education.

This study will extend Autor and Duggan's empirical analysis by including hypothesized determinants of health, including indicators of medical innovation, in models of the DI recipiency rate. In the next section we describe an econometric model of the DI recipiency rate. Section 3 discusses the measurement of a key variable in this model: the mean vintage of prescription drugs consumed. Section 4 presents descriptive statistics and explores the reasons for interstate variation in the growth in Medicaid drug vintage. Estimates of the model of the DI recipiency rate are presented in Section 5. The final section provides a summary and conclusions.

[4] There are two important aspects of program generosity: the probability that a person of given health status qualifies for benefits, and the benefits replacement rate.

2. Econometric model of the DI recipiency rate

To examine the effect of pharmaceutical innovation on the DI recipiency rate, controlling for DI program generosity, labor market conditions, age, education, and behavioral risk factors, we will estimate models of the following form, using longitudinal state-level data:

$$F^{-1}(N\_DISAB_{st} / POP20\_64_{st}) = \beta_1 RX\_VINT_{st} + \beta_2 \ln(WAGE_{st}) + \beta_3 \ln(EMP\_INDEX_{st}) + \beta_4 AGE_{st} + \beta_5 HS\_GRAD\%_{st} + \beta_6 COLLEGE\_GRAD\%_{st} + \beta_7 BMI\_GT25\%_{st} + \beta_8 SMOKING\%_{st} + \beta_9 AIDS_{st} + \alpha_s + \delta_t + \varepsilon_{st} \quad (1)$$

N_DISAB_{st}	= the number of workers[5] receiving DI benefits in state s in year t (t = 1995,…,2004)
$POP20\_64_{st}$	= the working-age (age 20-64) population in state s in year t
RX_VINT_{st}	= a measure of the vintage distribution of prescriptions filled in state s in year t
$WAGE_{st}$	= wages, salaries, and supplements per employee in state s in year t
EMP_INDEX_{st}	= an index of labor market conditions in state s in year t
AGE_{st}	= the mean age of the working-age (age 20-64) population in state s in year t
$HS\_GRAD\%_{st}$	= the % of adults who had a high school diploma or higher level of education in state s in year t
$COLLEGE\_GRAD\%_{st}$	= the % of adults who had a college diploma or higher level of education in state s in year t
$BMI\_GT25\%_{st}$	= the % of adults who were overweight or obese (Body Mass Index > 25) in state s in year t
$SMOKING\%_{st}$	= the % of adults who smoked in state s in year t
$AIDS_{st}$	= the number of AIDS (Acquired Immune Deficiency Syndrome) cases reported per 100,000 population in state s in year t-2
α_s	= a fixed effect for state s
δ_t	= a fixed effect for year t

$F^{-1}(\ )$ denotes the inverse of the standard normal cumulative distribution, so we are estimating a probit model with grouped data.[6] Since the model includes state and year fixed effects, it is a difference-in-differences model. Negative and significant estimates

[5] The DI program provides benefits to disabled workers, their spouses, and children (whether or not disabled). In 2003, 86% of disabled beneficiaries were workers. Our measure of the DI recipiency rate excludes spouses and children.

[6] Since N_DISAB_{st} / POP_{st} is bounded between zero and one, a linear model would not be appropriate.

of β_1 would indicate that, *ceteris paribus*, states with above-average increases in drug vintage had below-average increases in the DI recipiency rate. All models will be estimated via weighted least-squares, weighting by POP20_64. Clustered (within states) standard errors will be reported.

The principal contribution of this paper is the incorporation of the drug vintage measure in the model of DI recipiency. Measurement of drug vintage will be discussed in detail in the following section. First we will briefly discuss the reasoning behind and measurement of the other explanatory variables in eq. (1).

Wages. Autor and Duggan observed that "the DI benefits formula is progressive but is not indexed to regional wage levels. As a result, *workers in low wage states face significantly higher earnings replacement rates*" (emphasis added). Hence, states with lower wage growth would have higher growth (or smaller declines) in earnings replacement rates, hence higher expected growth in the DI recipiency rate.

Labor market conditions. Our measure of labor market conditions in state s in year t is similar to the one used by Autor and Duggan, which followed the approach developed by Bartik (1991) and employed by Blanchard and Katz (1991) and Bound and Holzer (2000). The index of labor market conditions exploits cross-state differences in industrial composition and national-level changes in employment to predict individual state employment growth. It is calculated as follows:

$$EMP\_INDEX_{st} = \Sigma_i \, EMP_{i,s,1995} \, (EMP_{i,US,t} / EMP_{i,US,1995}) / \Sigma_i \, EMP_{i,s,1995}$$

where

$EMP_{i,s,1995}$ = employment in industry i in state s in 1995
$EMP_{i,US,t}$ = employment in industry i in the U.S. in year t
$EMP_{i,US,1995}$ = employment in industry i in the U.S. in 1995

This methodology predicts what each state's change in employment would be if industry level employment changes occurred uniformly across states and state-level industrial composition was fixed in the short term. Accordingly, states with a relatively large share of workers in declining industries will have predicted employment declines, while those states differentially employing workers in growing industries will have predicted increases. Provided that national industry growth rates (excluding own state industry

employment) are uncorrelated with state level labor supply shocks, this approach will identify plausibly exogenous variation in state employment.

Age. As shown in Figure 1, the probability of being a DI recipient rises sharply with age. Therefore, an increase in the mean age of the working-age population is expected to increase the DI recipiency rate.

Education. Autor and Duggan provide evidence that the DI earnings replacement rate is inversely related to education; see Figure 2. A large body of evidence also suggests that more educated people are healthier, *ceteris paribus*. For both reasons, an increase in educational attainment is expected to reduce the DI recipiency rate.

Behavioral risk factors. High BMI, smoking participation, and HIV/AIDS infection are generally considered to be risk factors that reduce health status. Lichtenberg (2010) found that changes in life expectancy were inversely correlated across states with changes in all three of these variables during the period 1991-2004.

3. Measurement of drug vintage

All of our measures of drug vintage will be based on data on utilization of outpatient drugs paid for by state Medicaid agencies, combined with data on the initial FDA approval dates of the active ingredients of these drugs. According to the 2004 Medical Expenditure Panel Survey (MEPS), Medicaid paid for about 1/7 of all U.S. outpatient prescriptions in 2004.[7] We have data on virtually all of the approximately 4 billion Medicaid prescriptions dispensed during the period 1995-2004, by product,[8] state, and year,. Table 1 shows the distribution of these prescriptions by therapeutic group, as defined in RED BOOK Drug References.[9] There are 30 therapeutic groups, but the three largest account for about half of all prescriptions, and the six largest account for about three-quarters of all prescriptions.

Since people with less education and fewer skills are most at risk to enroll in the DI program, drugs used by the Medicaid population might be more relevant to disability

[7] The average price of Medicaid prescriptions ($69.40) was 8% higher than the average price of non-Medicaid prescriptions ($64.36).
[8] There are currently about 46,000 products.
[9] http://www.micromedex.com/products/redbook/ Therapeutic Group is an aggregation of Therapeutic Class values.

enrollment than drugs used by the population in general. For example, mental disorders was the diagnostic group that accounted for the largest fraction (33.5%) of disabled workers in 2004,[10] and MEPS data indicate that the fraction of 2004 Medicaid prescriptions that were used to treat mental disorders was 64% higher than the fraction of 2004 non-Medicaid prescriptions that were used to treat mental disorders (12.1% vs. 7.4%).

It might still be preferable to use data on all (non-Medicaid as well as Medicaid) prescriptions utilized, but state-level data on non-Medicaid prescriptions are not available over a sufficiently long period of time.[11] Lichtenberg (2010) presented evidence that, in six important classes of drugs,[12] 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 rx's tended to increase more in states with larger increases in the vintage of Medicaid rx's. This strong positive correlation may be partly attributable to the existence of spillovers from Medicaid to non-Medicaid prescribing. Wang et al (2003) found that Maine's Medicaid drug formulary generated spillover effects in cash and other third-party payer markets, with somewhat stronger effects in the cash market. Similarly, Virabhak and Shinogle (2005) observed that "the effects of Medicaid preferred drug lists on prescribing behavior extend beyond the Medicaid population."

We will use four different measures of drug vintage. The first two are based on the following measure of mean ingredient FDA initial approval year,[13] by therapeutic group, state, and year:

$$RX\_YEAR_{gst} = \Sigma_p \, N\_RX_{pgst} \, FDA\_YEAR_p / \Sigma_p \, N\_RX_{pgst} \qquad (2)$$

where

RX_YEAR_{gst} = the utilization-weighted average FDA approval year of the

[10] http://ssa.gov/policy/docs/statcomps/di_asr/2006/table21.xls

[11] Lichtenberg and Sun (2007) used data on all (Medicaid and non-Medicaid) prescriptions dispensed by a large retail pharmacy chain, but these data were only available for the period September 2004–December 2006.

[12] The six therapeutic classes of drugs were: antidepressants, antihypertensives, cholesterol-lowering drugs, diabetic drugs, osteoporosis/menopause drugs, and pain management medications.

[13] Data on FDA approval dates of new molecular entities (NMEs) from 1939 to 1998 were obtained via a Freedom of Information Act request to the FDA. Data on more recent NMEs and (beginning in 2004) new biologics were obtained from CDER Drug and Biologic Approval Reports (http://www.fda.gov/Cder/rdmt/default.htm). FDA approval dates of ingredients contained in about 15% of Medicaid prescriptions could not be determined.

active ingredients contained in Medicaid prescriptions in therapeutic group g in state s in year t

N_RX_{pgst} = the number of Medicaid prescriptions for drug product p in therapeutic group g in state s in year t

FDA_YEAR_p = the year in which the FDA first approved the active ingredient of product p[14]

This calculation yields 30 vintage measures (one for each therapeutic group) in each state in each year. Figure 3 shows the mean vintage of the five largest therapeutic groups of Medicaid prescriptions. In principle, one could include several of these vintage measures in a model of the DI recipiency rate. But therapeutic-group-specific vintage measures exhibit strong positive correlation—states with rapidly increasing vintage of some therapeutic groups tend to have rapidly increasing vintages of other therapeutic groups. Hence including several vintage measures would pose a problem of multicollinearity. It is therefore desirable to estimate models with single measures of drug vintage.

An obvious candidate is simply the weighted average of the therapeutic-group-specific vintage measures, weighted by the number of prescriptions in the therapeutic group:

$$RX\_YEAR_{st} = \Sigma_g \, N\_RX_{.gst} \, RX\_YEAR_{gst} / \Sigma_g \, N\_RX_{.gst} \qquad (3)$$

where

$$N\_RX_{.gst} = \Sigma_p \, N\_RX_{pgst}$$

RX_YEAR_{st} can change from one year to the next for two reasons (within- and between-group changes): within-therapeutic-group changes in drug vintage, and changes in the mix of drugs consumed. For example, Figure 3 shows that in 1995, the mean vintage of central nervous system (CNS) drugs was about 10 years lower than the mean vintage of cardiovascular drugs. If the number of cardiovascular prescriptions increased faster than the number of CNS drugs, this would cause RX_YEAR_{st} to increase, even if the vintage of drugs within each class remained unchanged.

We can construct a second vintage measure that eliminates the effect of changes in the mix of drugs consumed:

[14] For combination (multi-ingredient) products, we use the *mean* of the FDA approval years of the active ingredients.

$$RX\_YEAR\_WITHIN_{st} = \Sigma_g N\_RX_{.gs.} RX\_YEAR_{gst} / \Sigma_g N\_RX_{.gs.} \quad (4)$$

where

$$N\_RX_{.gs.} = \Sigma_t N\_RX_{.gst}$$

This is also a weighted average of the therapeutic-group-specific vintage measures, weighted by the number of prescriptions in the therapeutic group. But rather than using year-specific utilization weights, this measure uses fixed utilization weights, based on utilization of drugs within the state over the entire decade (1995-2004). Eliminating the effect of changes in the mix of drugs consumed may not be appropriate—changes in disability may depend on between-therapeutic-group as well as on within-therapeutic group changes in vintage—but determining the effect on our estimates of doing so is of interest.

The next two vintage measures we will use are similar to the first two, but instead of being based on a continuous measure of ingredient vintage (FDA approval year), they are based on a binary measure: whether or not the ingredient was first approved after 1990. The effect of FDA approval year on health may not be linear. Also, drugs approved after 1990 are far more likely to be patent-protected (hence more expensive) than previously-approved drugs, so specifically examining the effect of recently-approved drugs seems worthwhile.

Let us define a measure (analogous to that in eq. (2)) of the new (post-1990) ingredient share of prescriptions, by therapeutic group, state, and year:

$$RX\_POST1990\%_{gst} = \Sigma_p N\_RX_{pgst} POST1990_p / \Sigma_p N\_RX_{pgst} \quad (5)$$

where

$RX\_POST1990\%_{gst}$ = the fraction of Medicaid prescriptions in therapeutic group g in state s in year t that contained active ingredients first approved by the FDA after 1990

$POST1990_p$ = 1 if the year in which the active ingredient in product p was first approved by the FDA was > 1990
= 0 if the year in which the active ingredient in product p was first approved by the FDA was ≤ 1990

The new-ingredient share of prescriptions, by state and year, is:

$$RX\_\ POST1990\%_{st} = \Sigma_g\ N\_RX_{gst}\ RX\_POST1990\%_{gst} / \Sigma_g\ N\_RX_{gst} \quad (6)$$

The measure of the new-ingredient share of prescriptions that eliminates the effect of changes in the mix of drugs consumed is:

$$RX\_\ POST1990\%\_WITHIN_{st} = \Sigma_g\ N\_RX_{gs.}\ RX\_POST1990\%_{gst} / \Sigma_g\ N\_RX_{gs.} \quad (7)$$

Autor and Duggan (2003) argued that the rise in DI recipiency was partly due to an increase in DI program generosity, including an increase in the probability that a person of given health status qualified for benefits. One might interpret the vintage of Medicaid drugs as an indicator of Medicaid program generosity. One might also expect there to be a positive correlation across states between changes in DI program generosity and changes in Medicaid program generosity. Therefore if other variables included in eq. (1) do not fully control for DI program generosity, the coefficient on Medicaid drug vintage is likely to be biased towards zero.

So far, our discussion of drug vintage has not accounted for the distinction between priority-review and standard-review drugs. When a drug is approved by the FDA's Center for Drug Evaluation and Research, it is classified as either a "priority-review" drug—one that offers a "significant improvement compared to marketed products, in the treatment, diagnosis, or prevention of a disease"—or a "standard-review" drug—one that "appears to have therapeutic qualities similar to those of one or more already marketed drugs."[15] This distinction suggests that there might also be a distinction between the *actual* vintage of a drug and its *effective* vintage. Suppose a (standard-review) drug approved in 2008 is "therapeutically equivalent" to a drug approved in 1998. Then the "effective vintage" of the drug is 1998, whereas its actual vintage is 2008. (The effective vintage of a priority-review drug is the same as its actual vintage.)

More generally,

$$V^*_d = V_d - STD_d\ \Delta_d$$

where

V^*_d = the effective vintage of drug d
V_d = the actual vintage of drug d

[15] http://www.fda.gov/Cder/rdmt/InternetNME08.htm

STD_d = 1 if drug d is a standard-review drug
= 0 if drug d is a priority-review drug
Δ_d = the difference between the FDA approval year of standard-review drug d and the FDA approval year of the earliest drug with similar therapeutic qualities

If Δ_d were known, we could base all of our vintage measures on effective vintage rather than actual vintage. Unfortunately, the FDA does not identify the previously-marketed drugs to which standard-review drugs are considered similar, so data on Δ_d are not available. However suppose, for simplicity, that Δ_d were the same for all standard-review drugs: $\Delta_d = \Delta$, for all d. Then

$$V^*_d = V_d - STD_d \Delta$$

The (unweighted or utilization-weighted) average effective vintage of all drugs is then

$$V^* = V - STD\% \Delta$$

where STD% = the fraction of drugs that are standard-review drugs. Then, if the "true model" of health is

$$HEALTH = \beta V^* + \text{other variables}$$

we should estimate models of the form

$$HEALTH = \beta V - (\beta \Delta) STD\% + \text{other variables}$$
$$= \beta V + \gamma STD\% + \text{other variables} \quad (8)$$

where $\gamma = -(\beta \Delta)$. In other words, controlling for mean actual vintage and other variables, health should be inversely related to the fraction of drugs that are standard-review drugs. We will therefore estimate models that include $STD\%_{st}$: the fraction of prescriptions in state s in year t that were for standard-review drugs.

In principle, health status may depend on the mean vintage of all medical goods and services, not just drugs. Unfortunately, measuring the mean vintage of medical devices and procedures is far more challenging than measuring the vintage of drugs. Longitudinal, state-level data on utilization by working-age Americans of specific devices and procedures are not available. Moreover, government regulation of devices differs from its regulation of drugs, and procedures are largely unregulated, so it is difficult to determine the date of first use of most devices and procedures.

If pharmaceutical and non-pharmaceutical innovation are "complements" (i.e., they are positively correlated across states), estimates of β_1 could be biased away from

zero. On the other hand, if pharmaceutical and non-pharmaceutical innovation are "substitutes" (i.e., they are negatively correlated across states), estimates of β_1 could be biased towards zero. Lichtenberg (2009) provided some evidence about the sign of the correlation between pharmaceutical and non-pharmaceutical cardiovascular disease innovation across states.[16] All estimates of the correlation coefficients were negative, although only one was significant. This suggests that pharmaceutical and non-pharmaceutical cardiovascular disease innovation may be substitutes rather than complements. Therefore, failure to control adequately for non-pharmaceutical medical innovation may be more likely to bias estimates of β_1 towards zero than away from zero.[17]

4. Descriptive statistics and factors associated with Medicaid drug vintage

Sample mean values of the variables, by year, are shown in Table 2. (Sample mean values of the variables, by state, are shown in Appendix Table 1.) As noted earlier, the ratio of the number of workers receiving DI benefits to the working-age population increased 30% from 1995 to 2004, from 2.6% to 3.4%. The mean values of RX_YEAR and RX_YEAR_WITHIN both increased by about 7 years. The fraction of prescriptions that contained post-1990 active ingredients increased from 11% in 1995 to about 39% in 2004, both overall and within therapeutic groups. Smoking participation declined slightly, the fraction of the population that was overweight or obese increased about 20%, and the number of AIDS case reports per 100,000 population (lagged two years) declined by 73%. The mean age of the working-age population increased by 1.3 years; mean educational attainment also increased.

Before presenting estimates of eq. (1), which will provide evidence about the effect of drug vintage on DI recipiency, controlling for other factors, it is worth

[16] The measure of non-pharmaceutical cardiovascular disease innovation he used was the fraction of Medicare major cardiovascular surgical procedures with procedure codes established by the American Medical Association after 1990 or 1995.

[17] Lichtenberg (2007) found that controlling for a measure of *non-medical* innovation—the fraction of state residents who used a computer at home—did not affect estimates of the effect of drug vintage on life expectancy.

considering which, if any, of these factors are associated with drug vintage.[18] If drug vintage is highly correlated with a number of these other factors, it may be difficult to identify its effect on disability. Table 3 presents regressions of the four alternative drug vintage measures on the other explanatory variables in eq. (1). We also include an additional regressor: the log of per capita tax revenue in state s in year t. Since new drugs tend to be more expensive than old drugs, it is plausible that states with lower growth in per capita tax revenue would have smaller increases in Medicaid drug vintage (due, for example, to adoption of more restrictive formularies).

The dependent variable in column 1 is RX_YEAR, the mean initial FDA approval year of the active ingredients contained in Medicaid prescriptions. Only one variable in this equation has a coefficient that is significant at the 5% level: the AIDS incidence rate. The negative sign indicates that states whose AIDS incidence rates fell more slowly than average had smaller increases in Medicaid drug vintage. A similar result is obtained in column 2, where we analyze within-therapeutic-group changes in drug mean FDA approval year. The AIDS coefficient is also negative and significant in columns 3 and 4, where we analyze total and within-therapeutic-group changes in the new (post-1990) share of prescriptions. In those two equations, the per capita tax coefficient is positive and significant. This suggests that less financially constrained state governments may make newer drugs more available to Medicaid patients.

At first glance, a significant negative effect of AIDS incidence on drug vintage might seem surprising, since most drugs used to treat AIDS were approved in the mid 1990s. However, high AIDS incidence imposes a substantial burden on state Medicaid budgets. Bhattacharya et al (2003) estimated that almost half of U.S. residents with HIV/AIDS are insured by Medicaid. Duggan and Evans (2008) estimated that in California during the period 1994-2003, average annual Medicaid medical expenditure (the sum of pharmaceutical, outpatient and inpatient expenditure) per AIDS patient was about $18,800. Figure 4 shows that, despite the fact that the number of new AIDS cases declined by 69% from 1993 to 2002, national expenditure on HIV drugs increased almost seventeen-fold during that period. Lichtenberg (2006b) and Duggan and Evans (2008)

[18] Drug vintage is an indicator of the nature and perhaps quality of pharmaceutical treatment. Evaluation of the factors that affect (the probability of) treatment is often necessary to obtain unbiased estimates of treatment effects. See Dehejia and Wahba (2002).

both provide evidence that part of the increase in drug costs was offset by a reduction in inpatient costs resulting from use of newer drugs, and that the new HIV drugs were quite cost effective, by conventional standards. Nevertheless, the Medicaid budgets of states with slowly-declining numbers of AIDS cases would have been under greater stress than the Medicaid budgets of states with rapidly-declining numbers of AIDS cases. States in the former category may have been more likely to restrict access to new drugs.

Fortunately, even at its peak in 1993, the number of new U.S. AIDS cases (about 80,000) was too small to have a substantial direct effect on the aggregate DI recipiency rate. However, the significant negative association between AIDS incidence and Medicaid drug vintage suggests that AIDS incidence could have a positive *indirect* effect on the aggregate DI recipiency rate. High AIDS incidence may have increased disability rates among patients with other conditions by causing their access to newer treatments to be restricted.

5. Estimates of the model of the DI recipiency rate

Estimates of our model of the DI recipiency rate are shown in Table 4. The only difference between the six equations is the measure(s) of drug vintage used. The vintage measure in column 1 is RX_YEAR, the mean initial FDA approval year of the active ingredients contained in Medicaid prescriptions. The coefficient on this variable is negative and highly significant, which is consistent with the hypothesis that states that had larger increases in drug vintage had smaller increases in the DI recipiency rate, conditional on the other variables included. The coefficient on the average wage rate is also negative and highly significant, and this may be because DI earnings replacement rates declined most (or grew more slowly) in states with higher wage growth. The coefficient on the index of labor market conditions (ln(EMP_INDEX)) has the expected negative sign, but is not statistically significant.[19] The coefficients on the three behavioral risk factor variables (SMOKING%, BMI_GT25%, and AIDS) have the

[19] When we estimate a linear model (in which the dependent variable is (N_DISAB / POP20_64)) rather than a probit model, the coefficient on ln(EMP_INDEX) is negative and highly significant.

expected positive signs, but none are statistically significant.[20] The coefficient on the mean age of the working-age population is positive and significant, which is consistent with the cross-sectional data shown in Figure 1: the probability of receiving DI benefits rises sharply with age. The coefficient on HS_GRAD% (the % of adults who had a high school diploma or higher level of education) is not significant, but the coefficient on COLLEGE_GRAD% (the % of adults who had a high school diploma or higher level of education) is negative and significant. This may be due to the fact that the DI earnings replacement rate is inversely related to education (Figure 2), and also that more educated people are healthier, *ceteris paribus*.

As discussed above, under certain assumptions health (and disability) should depend on STD%—the fraction of prescriptions that are for standard-review (as opposed to priority-review) drugs—as well as on the mean FDA approval year. This variable is included in the equation in column 2 of Table 4. Its coefficient has the expected positive sign, but it is not statistically significant. This may be due to invalidity of the assumption which allowed us to derive eq. (8): that the difference between the FDA approval year of a standard-review drug and the FDA approval year of the earliest drug with similar therapeutic qualities was the same for all standard-review drugs.

In columns 3 and 4, RX_YEAR is replaced by RX_YEAR_WITHIN: we analyze the effect of within-therapeutic class, rather than total, changes in mean FDA approval year.[21] In column 5, the drug vintage measure is RX_POST1990%: the fraction of prescriptions that contained post-1990 ingredients. Column 6 examines the effect of within-therapeutic class, rather than total, changes in the fraction of prescriptions that contained post-1990 ingredients.

The implications of all six models are virtually identical. In every case, i.e. regardless of the precise definition of drug vintage, there is a significant inverse relationship between disability recipiency and Medicaid drug vintage.[22] Disability

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[20] Lichtenberg (2007) found that all three of these variables had significant negative effects on life expectancy.

[21] In column 4, STD% is replaced by STD%_WITHIN.

[22] We also estimated models that included measures of the vintage of drugs paid for by Medicare. These are primarily drugs administered by providers (e.g. chemotherapy) to elderly patients. Lichtenberg (2007) found that both Medicaid and Medicare drug vintage has a positive effect on life expectancy (at birth and at age 65). But the effect of Medicare drug vintage on disability in the working-age population is not statistically significant.

recipiency is also consistently inversely related to the average wage rate and COLLEGE_GRAD%, directly related to mean age, and unrelated to the other variables.

As shown in Figure 3 and Table 2, the mean vintage of Medicaid prescriptions increased during the sample period. The existence of a significant inverse relationship between disability recipiency and drug vintage implies that, if mean drug vintage had not increased—i.e., if people used the same drugs in 2004 as they had used in 1995—the DI recipiency rate would have increased more than it actually did. The "predicted" (or counterfactual) disability rate in year t (t = 1996,…,2004), in the absence of any increase in vintage after 1995, may be calculated as follows:

$$DI\_RATE\_PRED_t = F\,[F^{-1}(DI\_RATE_t) - \beta_1\,(RX\_VINT_t - RX\_VINT_{1995})]$$

The precise estimates of $DI\_RATE\_PRED_t$ obviously depend on which measure of RX_VINT (RX_YEAR, RX_YEAR_WITHIN, RX_POST1990%, or RX_POST1990%_WITHIN) we use, and on the corresponding estimate of β_1 (the RX_VINT coefficients in columns 1, 3, 5, or 6 of Table 4). But the estimates of $DI\_RATE\_PRED_t$ based on different measures of RX_VINT turn out to be quite similar. Figure 5 shows the *mean* of the estimates of $DI\_RATE\_PRED_t$ implied by the four different measures of RX_VINT, along with the actual DI recipiency rate.

From 1995 to 2004, the actual disability rate increased 30%, from 2.62% to 3.42%. The estimates in Table 4 imply that in the absence of any post-1995 increase in drug vintage, the increase in the disability rate would have been 30% larger: the disability rate would have increased 39%, from 2.62% to 3.65%. In 2004, the U.S. working-age population was 175.8 million. Hence the estimates imply that in the absence of any post-1995 increase in drug vintage, about 418,000 (= 175.8 million * (3.65% - 3.42 %)) more working-age Americans would have been DI recipients.[23] In December 2004, the

[23] Estimates of the increase in the number of disabled workers in 2004 from each of the four drug vintage measures are as follows:

rx_year	378,199
rx_year_within	395,518
rx_post1990%	431,525
rx_post1990%_within	467,009

average monthly benefit for disabled workers was $894.10.[24] This implies that in the absence of any post-1995 increase in drug vintage, Social Security benefits paid to disabled workers in 2004 would have been about $4.5 billion (= 418,000 * 12 * $894.10) (= 175.8 million * (3.65% - 3.42 %)) higher.

6. Summary and conclusions

A number of scholars have argued that medical innovation has played a major role in the long-term decline in disability. Two previous studies have investigated whether, in general, the introduction and use of newer prescription drugs reduces disability. One was based on longitudinal data on a set of diseases; the other was based on cross-sectional data on individuals. In both cases, disability status was self-reported.

This paper has reexamined the question using longitudinal state-level data during the period 1995-2004. The disability measure we analyzed is the ratio of the number of workers receiving Social Security Disability Insurance (DI) benefits to the working-age population (the "DI recipiency rate"). A previous study investigated the behavior of the DI recipiency rate using longitudinal state-level data during the period 1978-1998, but that study did not include measures of pharmaceutical use or other potential determinants of health.

We performed an econometric analysis of the effect of pharmaceutical innovation on the DI recipiency rate, controlling for other potential determinants of health (age, education, and behavioral risk factors) and other factors (DI program generosity and labor market conditions) that previous investigators have identified as important influences on DI participation. The principal contribution of this paper was the incorporation of drug vintage measures in models of DI recipiency. All of our measures of drug vintage were based on complete data on utilization of outpatient drugs paid for by state Medicaid agencies, combined with data on the initial FDA approval dates of the active ingredients of these drugs. Medicaid pays for 1 in 7 U.S prescriptions.

We estimated models of the DI recipiency rate using alternative measures of drug vintage. The implications of all of the models were virtually identical. In every case, i.e.

[24] http://ssa.gov/policy/docs/statcomps/di_asr/2004/sect01c.html#table20

regardless of the precise definition of drug vintage, there was a significant inverse relationship between disability recipiency and drug vintage. Disability recipiency was also consistently inversely related to the average wage rate and the fraction of state residents with at least a college education, and directly related to mean age.

The existence of a significant inverse relationship between disability recipiency and drug vintage implies that, if mean drug vintage had not increased—i.e., if people used the same drugs in 2004 as they had used in 1995—the DI recipiency rate would have increased more than it actually did. From 1995 to 2004, the actual disability rate increased 30%, from 2.62% to 3.42%. The estimates imply that in the absence of any post-1995 increase in drug vintage, the increase in the disability rate would have been 30% larger: the disability rate would have increased 39%, from 2.62% to 3.65%. This means that in the absence of any post-1995 increase in drug vintage, about 418,000 more working-age Americans would have been DI recipients, and that Social Security benefits paid to disabled workers in 2004 would have been about $4.5 billion higher.

We also explored the reasons for interstate variation in the growth in Medicaid drug vintage. Some estimates indicated that less financially-constrained state governments—those with higher growth in per capita tax revenue—may have made newer drugs more available to Medicaid patients. But the variable that had the greatest influence on Medicaid drug vintage was the AIDS incidence rate: states whose AIDS incidence rates fell more slowly than average had smaller increases in Medicaid drug vintage. This may be because the Medicaid budgets of states with slowly-declining numbers of AIDS cases were under greater stress than the Medicaid budgets of states with rapidly-declining numbers of AIDS cases. High AIDS incidence may have increased disability rates among patients with other conditions by causing their access to newer treatments to be restricted.

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Figure 1
Disabled workers as % of population, by age, 2006

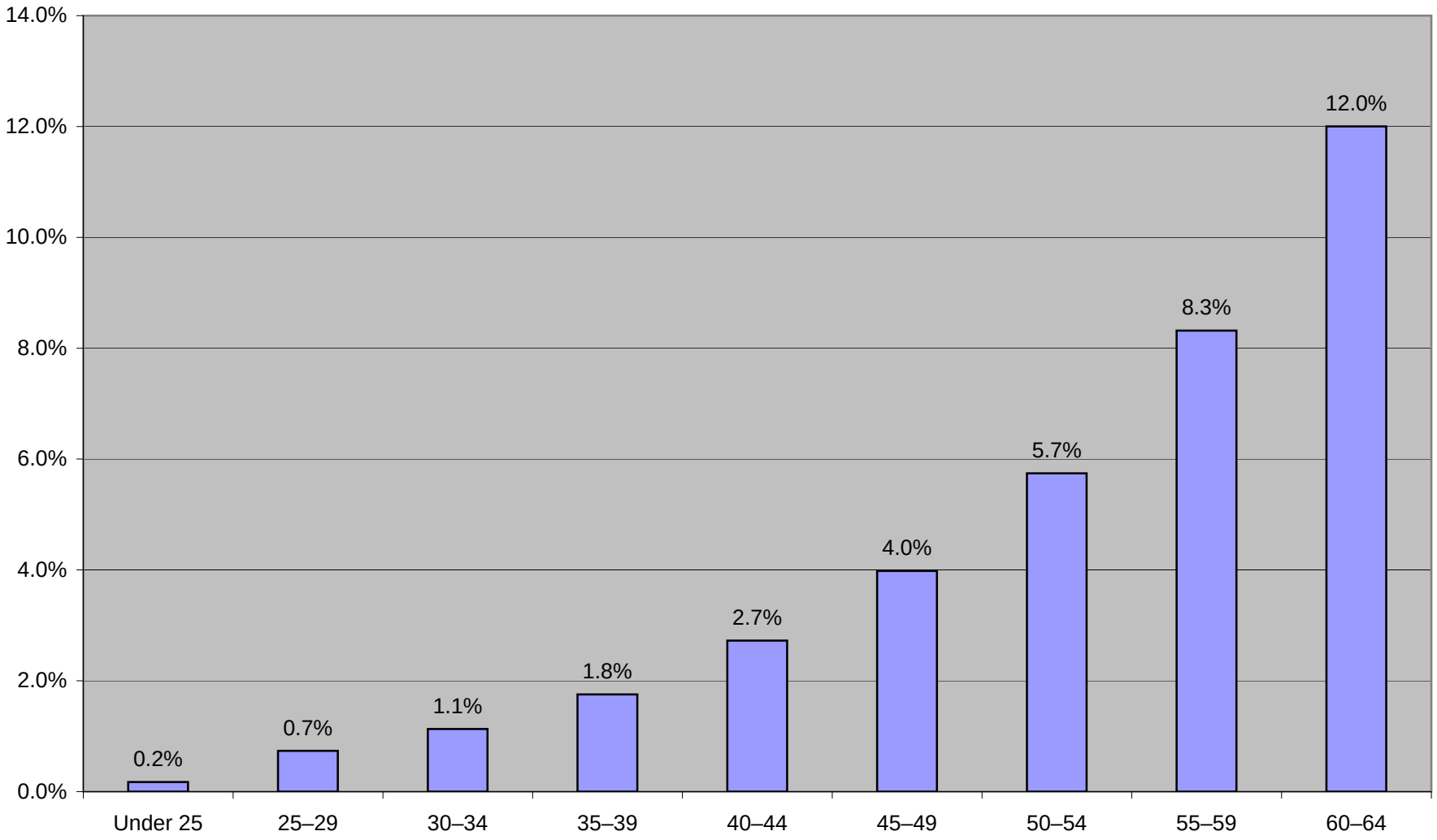
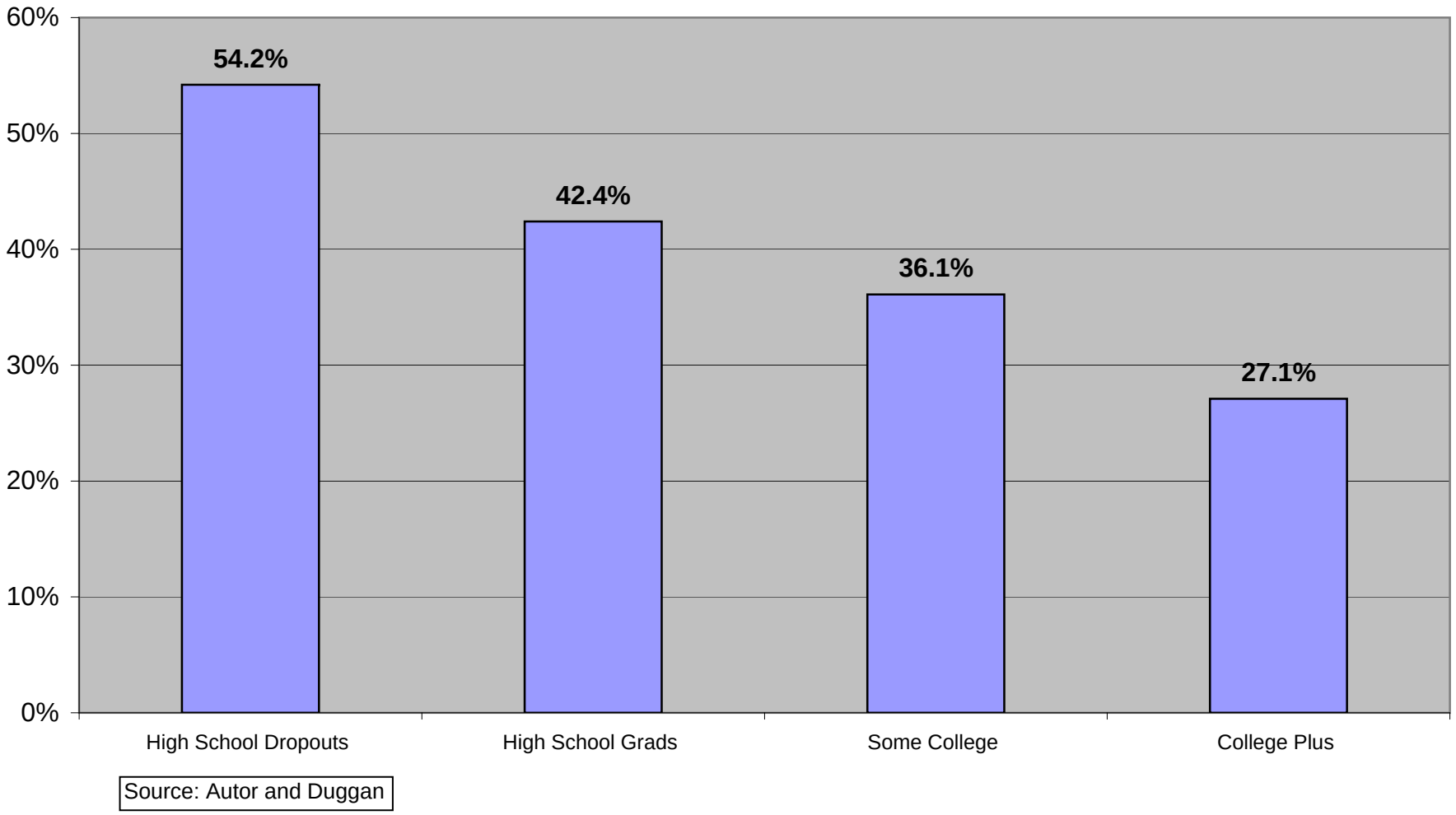


Figure 2
DI Earnings Replacement Rates for Males, by Education Group, 1996 (Lower Bound Estimates)



Source: Autor and Duggan

Figure 3
Mean vintage of five largest therapeutic groups of Medicaid prescriptions, 1995-2004

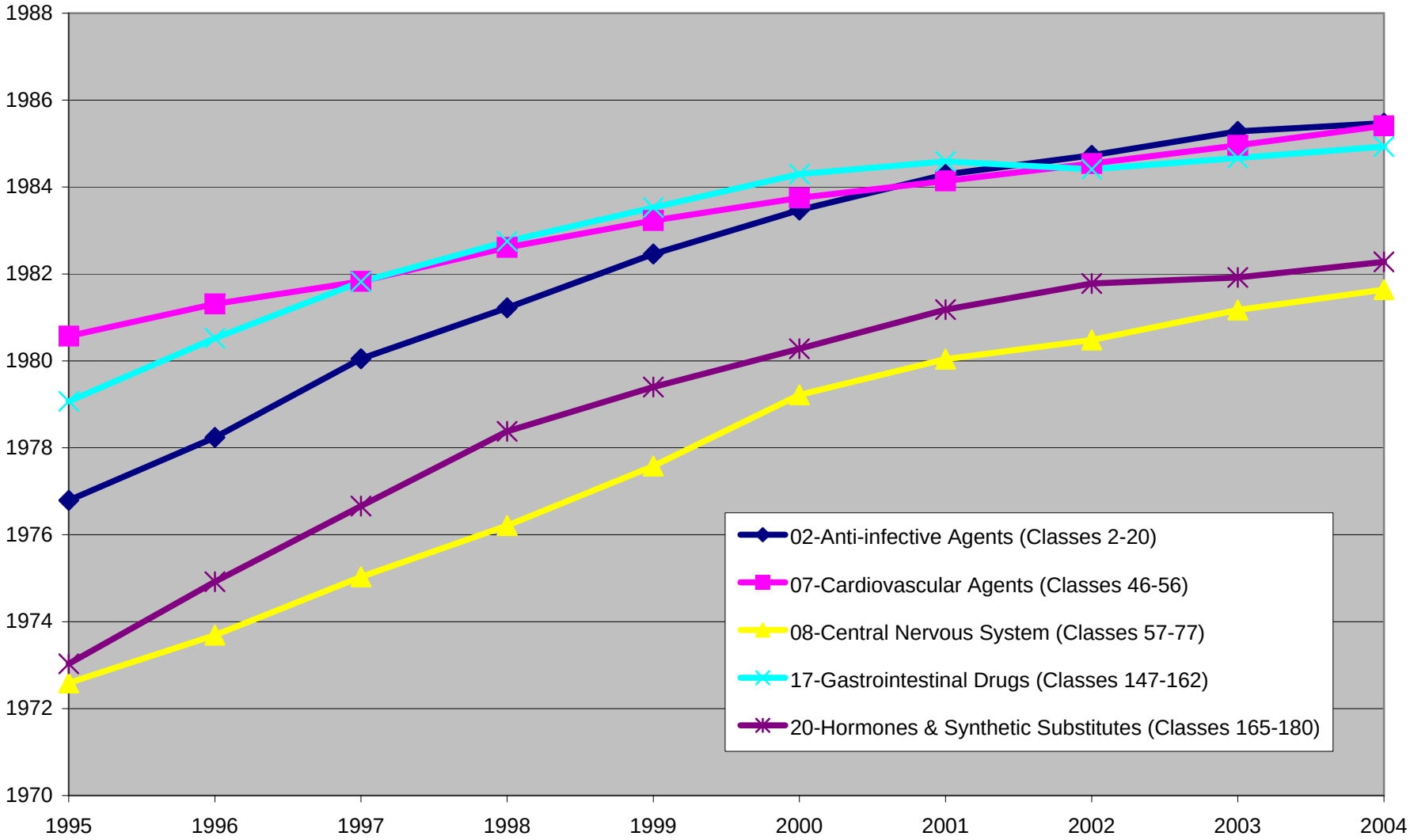
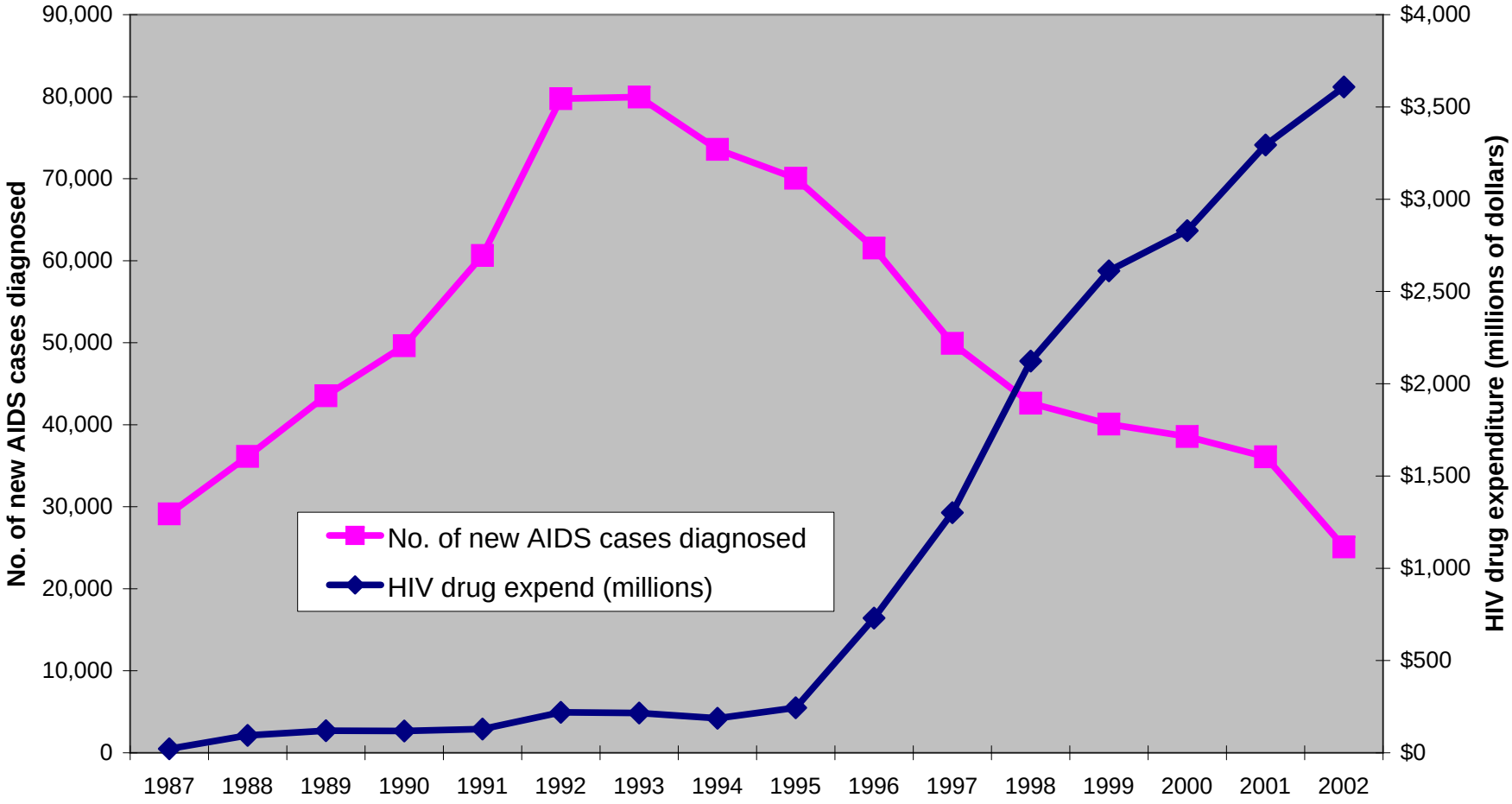


Figure 4
Number of new AIDS cases diagnosed, and HIV drug expenditure, 1987-2002



Sources:
Number of new AIDS cases diagnosed: AIDS Public Information Dataset U.S. Surveillance, http://wonder.cdc.gov/AIDSPublic.html
HIV drug expenditure: Unpublished IMS Health data

Figure 5
Predicted disability rate in year t (t = 1996,…,2004),
in the absence of any post-1995 increase in drug vintage

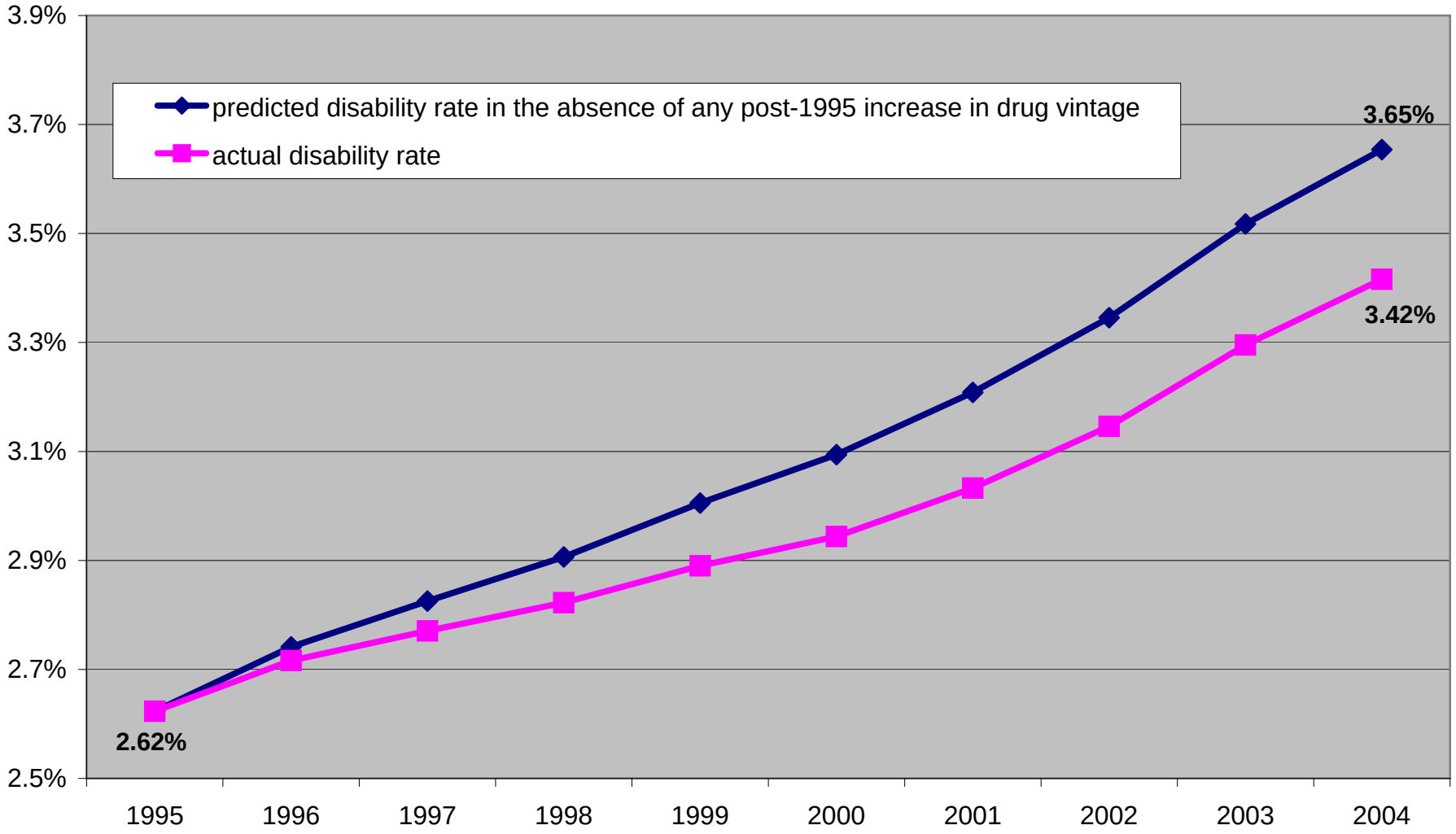


Table 1
Distribution of 1995-2004 Medicaid prescriptions by therapeutic group

THERGRP	total rx's, 1995-2004	cum. % of total rx's
08-Central Nervous System (Classes 57-77)	1,199,084,891	29.6%
07-Cardiovascular Agents (Classes 46-56)	544,287,003	43.0%
02-Anti-infective Agents (Classes 2-20)	401,851,402	52.9%
20-Hormones & Synthetic Substitutes (Classes 165-180)	383,320,122	62.4%
17-Gastrointestinal Drugs (Classes 147-162)	261,431,743	68.8%
13-Electrolytic, Caloric, Water (Classes 100-126)	247,416,383	74.9%
04-Autonomic Drugs (Classes 23-33)	233,261,309	80.7%
26-Skin & Mucous Membrane (Classes 190-213)	178,003,964	85.1%
01-Antihistamines & Comb. (Class 1)	146,539,065	88.7%
16-Eye, Ear, Nose Throat (Classes 132-146, 240)	119,588,044	91.6%
06-Blood Form/Coagul Agents (Classes 35-45)	90,671,733	93.9%
28-Vitamins & Comb (Classes 217-233)	72,037,837	95.7%
29-Unclassified Agents (Classes 234-236)	61,439,930	97.2%
15-Antituss/Expector/Mucolytic (Classes 128-131)	50,998,637	98.4%
27-Smooth Muscles Relaxants (Classes 214-216)	33,018,434	99.2%
03-Antineoplastic Agents (Classes 21-22)	14,664,684	99.6%
21-Immunosuppressants (Class 181)	4,703,256	99.7%
10-Dental Agents (Classes 79-83)	3,961,122	99.8%
31-Pharmaceutical Aids/Adjuvants (Class 238)	3,291,796	99.9%
23-Oxytoxics (Class 183)	886,784	99.9%
99-Other/unavailable	715,773	99.9%
22-Anesthetics, Local (Class 122)	660,620	100.0%
09-Contraceptive Cream/Foam/Devices (Classes 78)	423,131	100.0%
25-Serums, Toxoids, Vaccines (Classes 185-189)	402,055	100.0%
19-Heavy Metal Antagonists (Class 164)	350,321	100.0%
11-Diagnostic Agents (Classes 84-98, 239)	125,261	100.0%
30-Devices and Non-drug Items (Class 237)	96,806	100.0%
18-Gold Compounds (Class 163)	75,499	100.0%
05-Blood Derivatives (Class 34)	31,321	100.0%
14-Enzymes (Class 127)	30,881	100.0%
TOTAL	**4,053,369,807**	

Table 2

Sample means by year

year	working-age pop. (millions)	disability rate	rx_year	rx_year_within	rx_post1990 %	rx_post1990 %_within	std%	wage (thousands)	emp_index	smoking%	bmi_gt25%	aids	age	hs_grad%	college_grad %
1995	155.9	2.6%	1973.4	1973.6	11%	11%	56%	$33.5	1.00	22%	49%	30	39.9	82%	23%
1996	157.6	2.7%	1974.4	1974.6	14%	14%	55%	$34.5	1.02	23%	50%	27	40.1	82%	24%
1997	161.2	2.8%	1975.6	1975.7	18%	18%	55%	$35.8	1.04	23%	51%	25	40.3	82%	24%
1998	161.9	2.8%	1976.7	1976.6	22%	22%	55%	$37.7	1.07	23%	53%	22	40.5	83%	24%
1999	164.2	2.9%	1977.7	1977.6	26%	26%	56%	$39.2	1.09	23%	54%	17	40.6	83%	25%
2000	166.6	2.9%	1978.8	1978.7	30%	30%	56%	$41.5	1.12	22%	55%	15	40.7	84%	26%
2001	169.1	3.0%	1979.4	1979.3	33%	33%	57%	$42.7	1.12	23%	57%	14	40.9	84%	26%
2002	171.5	3.1%	1979.9	1979.8	36%	35%	58%	$44.1	1.12	22%	57%	13	41.0	84%	27%
2003	173.6	3.3%	1980.4	1980.2	38%	37%	59%	$45.8	1.13	21%	58%	12	41.1	85%	27%
2004	168.9	3.4%	1980.7	1980.5	39%	38%	60%	$48.2	1.15	20%	59%	8	41.3	85%	28%

Table 3
Examination of factors associated with Medicaid drug vintage

column	1	2	3	4
dependent variable	RX_YEAR	RX_YEAR_WITHIN	RX_POST1990%	RX_POST1990%_WITHIN
ln(WAGE)	5.6946	3.1704	0.7907	0.7371
Z	1.15	0.96	1.19	1.22
ProbZ	0.2495	0.336	0.2358	0.2215
ln(EMP_INDEX)	-2.4066	-4.6639	-1.6408	-1.7042
Z	-0.22	-0.56	-1.24	-1.32
ProbZ	0.8269	0.5783	0.2149	0.1878
SMOKING%	-6.6307	-6.4733	-0.549	-0.5892
Z	-1.50	-1.59	-1.20	-1.38
ProbZ	0.1345	0.1115	0.2309	0.169
BMI_GT25%	-6.9658	-3.6101	-0.9185	-0.7329
Z	-1.51	-1.21	-1.53	-1.40
ProbZ	0.1307	0.228	0.1266	0.1629
AIDS	**-0.0357**	**-0.0292**	**-0.0054**	**-0.0056**
Z	**-2.06**	**-2.65**	**-2.29**	**-2.56**
ProbZ	**0.0394**	**0.0081**	**0.0219**	**0.0105**
AGE	0.8898	0.9441	0.0647	0.0728
Z	1.10	1.51	0.70	0.86
ProbZ	0.2727	0.1306	0.4834	0.3885
HS_GRAD%	-0.0494	-0.0206	-0.0064	-0.0062
Z	-0.74	-0.45	-0.77	-0.85
ProbZ	0.4606	0.6537	0.4439	0.3971
COLLEGE_GRAD%	-0.0025	0.0065	0.0019	0.0022
Z	-0.07	0.24	0.49	0.61
ProbZ	0.9433	0.8107	0.6257	0.5405
ln(TAX_POP)	1.4753	0.6765	**0.2594**	**0.209**
Z	1.80	1.26	**2.27**	**2.04**
ProbZ	0.0714	0.2076	**0.0231**	**0.0415**

All models include state and year fixed effects, and were estimated via weighted least-squares, weighting by POP20_64. Z-statistics and probability values are based on standard errors that were clustered (within states).

Table 4
Estimates of eq. (1), model of disability recipiency

column	1	2	3	4	5	6
drug vintage measure	RX_YEAR	RX_YEAR	RX_YEAR_WITHIN	RX_YEAR_WITHIN	RX_POST1990%	RX_POST1990%_WITHIN
rx_vint	**-0.0038**	**-0.0035**	**-0.0042**	**-0.0046**	**-0.1124**	**-0.1237**
Z	**-3.05**	**-2.51**	**-2.07**	**-2.20**	**-2.76**	**-2.22**
ProbZ	**0.0023**	**0.012**	**0.0384**	**0.0278**	**0.0058**	**0.0266**
std%		0.105		0.0855		
Z		1.20		0.55		
ProbZ		0.2308		0.5818		
ln(WAGE)	**-0.2202**	**-0.2125**	**-0.2303**	**-0.2264**	**-0.2327**	**-0.2334**
Z	**-2.56**	**-2.47**	**-2.75**	**-2.68**	**-2.80**	**-2.79**
ProbZ	**0.0104**	**0.0134**	**0.0059**	**0.0074**	**0.0051**	**0.0052**
ln(EMP_INDEX)	-0.292	-0.2934	-0.3083	-0.3136	-0.3216	-0.3278
Z	-0.87	-0.89	-0.92	-0.94	-0.96	-0.98
ProbZ	0.3825	0.3755	0.3553	0.3459	0.3368	0.326
SMOKING%	0.0194	0.0347	0.0167	0.0239	0.0212	0.0177
Z	0.23	0.44	0.20	0.29	0.26	0.21
ProbZ	0.817	0.66	0.8447	0.7714	0.7966	0.8314
BMI_GT25%	0.0087	0.0195	0.0168	0.025	0.0169	0.0195
Z	0.16	0.37	0.33	0.46	0.33	0.39
ProbZ	0.8691	0.7107	0.7436	0.646	0.7394	0.6997
AIDS	0.0003	0.0003	0.0003	0.0003	0.0002	0.0002
Z	1.18	1.29	1.16	1.26	0.94	0.81
ProbZ	0.2393	0.1961	0.246	0.2088	0.3479	0.4165
AGE	**0.0522**	**0.0499**	**0.0525**	**0.0515**	**0.0511**	**0.0516**
Z	**3.62**	**3.38**	**3.75**	**3.54**	**3.49**	**3.57**
ProbZ	**0.0003**	**0.0007**	**0.0002**	**0.0004**	**0.0005**	**0.0004**
HS_GRAD%	0.001	0.001	0.0011	0.0011	0.0011	0.0011
Z	0.91	0.86	1.01	0.99	1.02	0.99
ProbZ	0.3636	0.3896	0.3132	0.3235	0.3071	0.3241
COLLEGE_GRAD%	**-0.001**	**-0.0011**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
Z	**-2.34**	**-2.34**	**-2.23**	**-2.19**	**-2.27**	**-2.20**
ProbZ	**0.0193**	**0.0192**	**0.0257**	**0.0287**	**0.023**	**0.0276**

The dependent variable is F^{-1}(N_DISAB / POP20_64). All models include state and year fixed effects, and were estimated via weighted least-squares, weighting by POP20_64. Z-statistics and probability values are based on standard errors that were clustered (within states).

Appendix Table 1
Sample means by state

state	working-age pop. (millions)	disability rate	rx_year	rx_year_within	rx_post1990%	rx_post1990%_within	std%	wage	emp_index	smoking%	bmi_gt25%	aids	age	hs_grad%	college_grad%
Alabama	2.6	4.9%	1976.3	1976.3	24%	24%	59%	$36.0	1.08	23%	55%	11	40.8	79%	21%
Alaska	0.4	1.9%	1978.4	1978.4	30%	29%	56%	$45.7	1.10	28%	57%	5	40.0	91%	26%
Arizona	2.9	3.0%	.	.	.	.	.	$39.2	1.12	.	.	.	40.1	84%	24%
Arkansas	1.5	5.2%	1976.9	1976.8	25%	25%	59%	$32.1	1.08	26%	54%	9	40.9	79%	17%
California	20.0	2.2%	1976.7	1976.7	25%	25%	53%	$47.8	1.11	18%	50%	23	39.7	81%	28%
Colorado	2.6	2.3%	1978.3	1978.2	27%	27%	56%	$43.1	1.12	22%	45%	12	40.1	89%	34%
Connecticut	2.0	2.7%	1979.4	1979.4	30%	30%	55%	$53.3	1.11	21%	48%	24	41.1	86%	32%
Delaware	0.5	3.2%	1978.2	1978.2	29%	29%	59%	$44.9	1.11	25%	54%	27	40.6	85%	26%
DC	0.4	2.3%	1977.6	1977.6	26%	26%	54%	$69.1	1.10	19%	49%	161	39.0	83%	40%
Florida	9.1	3.4%	1979.1	1979.1	30%	29%	58%	$37.8	1.13	22%	51%	38	41.2	83%	23%
Georgia	5.0	3.2%	1977.0	1976.8	26%	26%	59%	$40.9	1.10	22%	55%	21	39.9	81%	24%
Hawaii	0.7	1.9%	1977.3	1977.2	24%	24%	54%	$40.1	1.10	19%	45%	14	40.4	87%	25%
Idaho	0.7	2.9%	1978.5	1978.4	30%	30%	58%	$33.3	1.10	20%	52%	3	40.5	86%	21%
Illinois	7.3	2.5%	1976.5	1976.6	24%	24%	56%	$45.5	1.11	23%	53%	15	40.3	85%	26%
Indiana	3.6	3.2%	1977.3	1977.2	25%	25%	59%	$37.7	1.09	26%	55%	8	40.5	84%	19%
Iowa	1.7	2.9%	1976.9	1976.9	24%	24%	56%	$34.0	1.09	22%	55%	3	40.9	88%	23%
Kansas	1.5	2.8%	1978.5	1978.5	29%	29%	55%	$35.7	1.10	22%	52%	6	40.4	88%	28%
Kentucky	2.4	5.3%	1976.7	1976.7	25%	25%	57%	$35.9	1.08	29%	55%	7	40.7	79%	20%
Louisiana	2.6	3.6%	1977.4	1977.3	27%	27%	58%	$35.0	1.11	24%	55%	21	40.3	78%	21%
Maine	0.8	4.7%	1978.4	1978.4	27%	26%	54%	$34.6	1.09	23%	53%	5	41.6	87%	22%
Maryland	3.2	2.2%	1978.4	1978.4	28%	28%	57%	$45.4	1.12	20%	52%	32	40.7	86%	34%
Massachusetts	3.8	3.3%	1978.1	1978.1	25%	25%	54%	$50.2	1.11	22%	48%	18	40.4	86%	33%
Michigan	5.8	3.2%	1978.1	1978.0	26%	26%	56%	$44.7	1.10	25%	56%	8	40.7	86%	22%
Minnesota	2.9	2.4%	1977.8	1977.7	25%	25%	56%	$42.0	1.10	21%	54%	5	40.5	90%	30%
Mississippi	1.6	5.3%	1978.1	1978.1	29%	29%	58%	$31.5	1.08	23%	57%	13	40.3	79%	20%
Missouri	3.2	3.9%	1978.1	1978.1	28%	28%	58%	$37.9	1.10	26%	54%	11	40.8	85%	25%
Montana	0.5	3.3%	1977.7	1977.6	26%	26%	56%	$31.2	1.10	22%	52%	3	41.5	89%	24%
Nebraska	1.0	2.7%	1977.4	1977.4	26%	26%	59%	$34.4	1.10	21%	54%	5	40.5	89%	24%
Nevada	1.2	2.7%	1978.6	1978.5	28%	28%	57%	$41.2	1.13	27%	51%	18	40.7	86%	21%
New Hampshire	0.7	3.2%	1977.7	1977.6	26%	26%	57%	$40.8	1.11	23%	50%	5	41.1	88%	30%
New Jersey	5.0	2.5%	1979.1	1979.1	30%	30%	57%	$51.1	1.11	20%	49%	33	41.0	86%	31%
New Mexico	1.0	3.2%	1977.0	1977.1	25%	25%	59%	$35.0	1.11	22%	50%	8	40.6	81%	23%
New York	11.3	3.0%	1978.3	1978.3	29%	29%	55%	$52.9	1.12	23%	50%	50	40.6	83%	28%
North Carolina	4.8	4.1%	1978.3	1978.2	29%	29%	59%	$37.5	1.08	24%	54%	11	40.4	79%	23%
North Dakota	0.4	2.5%	1978.0	1978.0	27%	27%	56%	$31.3	1.09	22%	56%	1	40.3	85%	23%
Ohio	6.6	3.0%	1977.7	1977.7	27%	27%	59%	$39.3	1.10	25%	54%	7	40.8	86%	23%
Oklahoma	2.0	3.4%	1978.2	1978.1	27%	27%	55%	$34.1	1.10	24%	53%	8	40.7	85%	22%
Oregon	2.0	2.8%	1977.7	1977.6	27%	26%	57%	$39.2	1.11	21%	52%	10	40.9	87%	26%
Pennsylvania	7.1	3.1%	1978.6	1978.6	28%	28%	58%	$41.1	1.10	24%	54%	15	41.2	85%	24%
Rhode Island	0.6	3.8%	1978.5	1978.4	27%	27%	56%	$40.0	1.11	23%	50%	14	40.4	80%	27%
South Carolina	2.4	4.4%	1978.4	1977.9	30%	29%	58%	$34.8	1.08	24%	54%	19	40.6	79%	21%
South Dakota	0.4	2.9%	1978.8	1978.7	28%	28%	56%	$30.4	1.09	22%	55%	2	40.7	87%	23%
Tennessee	3.4	4.1%	.	.	.	.	.	$35.0	1.07	26%	52%	11	40.5	79%	20%

state	working-age pop. (millions)	disability rate	rx_year	rx_year_within	rx_post1990%	rx_post1990%_within	std%	wage	emp_index	smoking%	bmi_gt25%	aids	age	hs_grad%	college_grad%
Texas	12.2	2.3%	1977.8	1977.7	27%	27%	59%	$41.6	1.11	22%	54%	19	39.7	78%	24%
Utah	1.2	1.8%	1977.7	1977.7	28%	28%	58%	$35.9	1.11	14%	49%	7	38.3	90%	27%
Vermont	0.4	3.5%	1977.9	1977.8	27%	27%	56%	$35.1	1.10	21%	49%	5	41.2	88%	29%
Virginia	4.3	3.0%	1977.5	1977.5	26%	26%	59%	$43.5	1.10	23%	52%	14	40.4	85%	31%
Washington	3.5	2.6%	1977.4	1977.4	25%	25%	56%	$45.0	1.11	22%	51%	11	40.6	90%	28%
West Virginia	1.1	5.8%	1977.5	1977.5	26%	26%	58%	$34.6	1.09	27%	57%	5	41.6	77%	15%
Wisconsin	3.1	2.6%	1977.6	1977.6	25%	25%	56%	$35.2	1.07	24%	55%	5	40.4	87%	23%
Wyoming	0.3	2.7%	1978.0	1978.0	29%	29%	57%	$34.2	1.10	23%	52%	2	41.1	91%	21%

Arizona does not cover drugs under the Medicaid Drug Rebate Program. Data for Tennessee are not available for the years 1995-1998.
http://www.cms.hhs.gov/MedicaidDrugRebateProgram/01_Overview.asp