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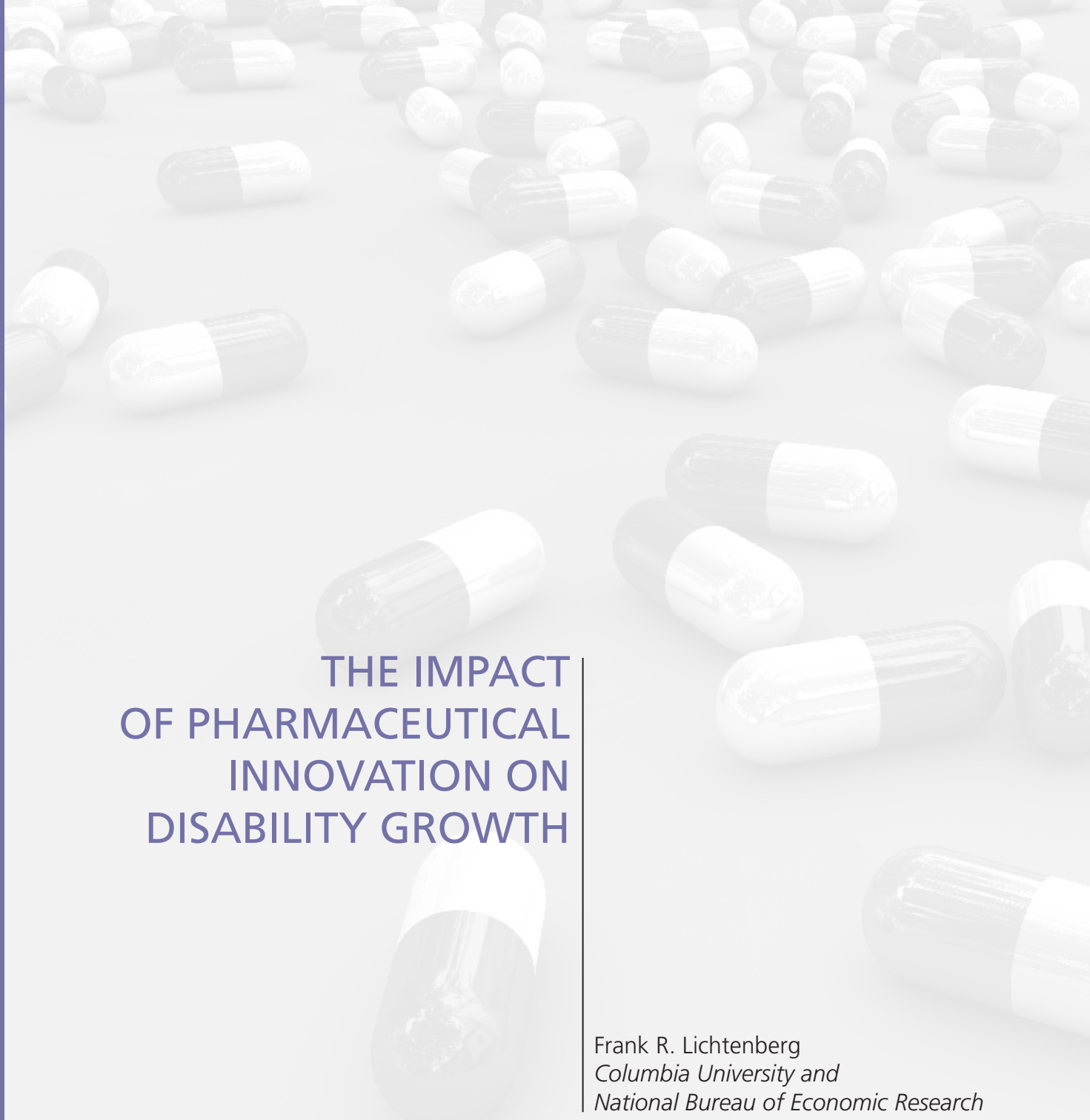

THE IMPACT OF PHARMACEUTICAL INNOVATION ON DISABILITY GROWTH

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HAVE NEWER DRUGS KEPT AMERICANS OFF DISABILITY ROLLS?

Rising numbers of Americans have been classified as disabled. In particular, between 1995 and 2004, the number of Americans receiving benefits under two federal disability programs—Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI)—rose 30 percent.

Policymakers, who face ever-rising costs and severe budget constraints, are searching for ways to reduce expenditures—or at least, to slow their rate of growth. In this regard, measures to keep working-age Americans off disability rolls—for instance, through access to medical innovations—should be particularly welcome.

The following report examines whether innovation in one form of medical treatment, prescription drugs, has helped reduce the growth in disability rates. Specifically, the report studies patterns in the dispensing of prescription drugs in forty-nine of the fifty states from 1995 to 2004, using data on Medicaid prescriptions in thirty therapeutic groups, which account for virtually all Medicaid medicines dispensed. The data includes the name of the drug and the year in which the U.S. Food and Drug Administration approved its active ingredient—what we call the drug's "vintage." For instance, Zocor's active ingredient, simvastatin, was approved in 1991, making 1991 the drug's vintage.

Medicaid covered about one in seven prescriptions written in the United States in 2004, and the vintages of Medicaid and non-Medicaid prescriptions are strongly correlated. Earlier studies have established that the fraction of the working-age population receiving disability benefits depends mainly on three variables: health status of the applicant; general labor market conditions; and the generosity of the disability programs. This study concludes that the vintage of drugs used by a state's residents—to be specific, how recently those drugs' active ingredient received FDA approval—qualifies as an additional factor in determining the size of that state's disability rolls. The study found that states in which the difference between average vintage of Medicaid prescriptions in 1995 and average vintage in 2004 was the largest—these being states in which pharmaceutical innovations were adopted quickly—had the smallest increases in disability rates.

For instance, in California, Idaho, Rhode Island, Maryland, and Connecticut, the five states in which the difference between average vintage in 1995 and average vintage in 2004 was largest (the movement always being from less recent to more recent), the number of disability recipients per 100,000 working-age people increased by 800. In Oklahoma, Alabama, Texas, Louisiana, and West Virginia, the five states in which the difference between average vintage in 1995 and average vintage in 2004 was smallest, the number of disability recipients per 100,000 working-age people increased by 1,400, a rate of increase that was 75 percent greater than it was in the first five states. This comparison controlled for behavior-related risk factors such as obesity and smoking as well as education, wage rates, and changes in average age.

By our estimates, if the average vintage of drugs prescribed since 1995 and paid for by Medicaid had not become more recent, the rate of increase at which working-age people were classified as disabled would have been 30 percent higher than it actually was, resulting in 418,000 additional people receiving disability payments in 2004. Social Security benefits paid to this population would have been an additional $4.5 billion.

Consequently, it is reasonable to conclude that access to pharmaceutical innovations has been responsible for keeping large numbers of U.S. residents off disability rolls who otherwise would have joined them.

Interestingly, fewer more recent—and apparently, more effective (and expensive)—drugs were prescribed in states with lower per-capita incomes than were prescribed in higher-income states, suggesting that financial constraints may be

limiting access to newer medicines, even though the therapeutic benefits of these medicines, which may, for instance, reduce the incidence of disability, might have the effect of offsetting their higher costs.

In addition, the vintage of all Medicaid prescriptions became more recent more slowly in states where AIDS/HIV infection rates remained higher than average. In this subset, it is possible that spending on expensive, though highly cost-effective, AIDS/HIV treatment is leaving less money available for relatively new drugs that treat other ailments. Policymakers may, in these cases, want to allocate additional funding to HIV prevention, which is much less expensive than treatment.

The states, as well as the federal government, have an economic incentive to minimize the number of people needing disability payments. Access to medical innovations such as newer prescription drugs can help ensure that even patients with chronic illnesses remain wage earners and taxpayers. Disability funding would then be reserved for those suffering from intractable conditions.

About the Author

FRANK LICHTENBERG currently serves as the Courtney C. Brown Professor of Business at the Columbia University Graduate School of Business as well as a research associate of the National Bureau of Economic Research. His work has focused on how new technologies affect the productivity of companies, industries, and nations. Lichtenberg's studies have ranged from the impact of pharmaceutical innovation to the effect of leveraged buyouts on efficiency and employment. This research has earned him numerous fellowships and awards, including the 1998 Schumpeter Prize and a 2003 Milken Institute Award for Distinguished Economic Research, as well as grants from the National Science Foundation, the National Institute of Standards and Technology, Merck and Co., the Fulbright Commission, and the Alfred P. Sloan Foundation. He has worked for several U.S. government agencies, including the Department of Justice and the Congressional Budget Office. He has also taught at Harvard University and the University of Pennsylvania.

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The Impact of Pharmaceutical Innovation on Disability Growth

Frank R. Lichtenberg

I. INTRODUCTION

It is widely recognized that some medical innovations, such as angioplasty to open clogged arteries, transplants for patients with organ failure, and antiviral drugs for HIV-infected patients, have saved and prolonged lives. But have medical innovations also reduced the rate and severity of disability due to chronic diseases or the normal aging process? Americans' chances of living independent, productive lives depend on the answer, but too little research into the relative value of particular kinds of intervention has been carried out, despite the consequences for our nation's economy and safety-net programs like Medicare.

The issue is becoming increasingly acute. Populations in advanced nations in North America, Asia, and Japan are getting significantly older—by 2030, approximately one in five Americans will be sixty-five or older, straining public and private health-care systems. Rapid increases in obesity in the United States and Europe may also burden health-care budgets, since obesity is a significant risk factor for diabetes, heart disease, and other chronic ailments.

Public and private health insurers in these nations will face difficult choices about how to allocate scarce resources for health-care spending. If, however, individuals' access to new medical innovations enables them to care for and support themselves longer than they could have otherwise, then perhaps governments should adopt

policies that promote access to those innovations and the development of additional ones.

A number of scholars have found that medical innovation has strongly contributed to the long-term decline in disability in the United States over the last century. In comparing data from the Civil War–era Union Army pension program with more recent data, Costa (2000) found that functional disability among men aged fifty to seventy-four (including difficulty in walking, difficulty in bending, paralysis, blindness in at least one eye, and deafness in at least one ear) in the United States fell at an average annual rate of 0.6% from the early twentieth century to the early 1990s and that 24%–41% of this decline was attributable to innovations in medical care. More recently, Manton et al. (2006) found that the prevalence of chronic disability among elderly Americans declined from 26.5% in 1982 to 19% in 2004–05 and hypothesized that biomedical interventions were, to some extent, responsible for reductions in its incidence and severity.

Biomedical innovation is, however, a broad category, and includes interventions ranging from improved training of physicians to the use of newer diagnostics, medical devices, and prescription drugs. Unfortunately, comprehensive data on the use of many of these technologies are unavailable.[1] But good data on one widely used type of medical innovation—prescription drugs—are available. Two previous studies have investigated whether the introduction and use of newer prescription drugs reduce disability. One study (Lichtenberg 2005) examined longitudinal data on a set of major chronic diseases such as hypertension, asthma, and diabetes in non-elderly patients from 1982 to 1996. It found that the larger the percentage increase in the 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.

The other study (Lichtenberg and Virabhak 2007) examined data on a large cross-section of individuals surveyed in 1997. It found that people using newer drugs had better post-treatment health than people using older drugs for the same condition, after controlling for pretreatment health, age, sex, race, marital status, education, income, and insurance coverage: they experienced fewer activity, social, and physical limitations; their own perception of their health status was more positive; and their lives were longer. The disability measures used in both these studies were self-reported and derived from household surveys (the National Health Interview Survey and the Medical Expenditure Panel Survey).[2]

In this paper, we reexamine whether the use of newer prescription drugs, one important type of medical innovation, reduces disability, using longitudinal state-level data on forty-nine states for the period 1995–2004.[3] The disability measure that we analyze is the ratio of the number of workers receiving Social Security Disability Insurance (DI) benefits to the working-age population.[4] Our measures of pharmaceutical innovation are based on complete data on utilization of outpatient drugs paid for by state Medicaid agencies, as well as data on the initial FDA approval dates of the active ingredients of these drugs, which allow us to assess the "vintage" of all prescriptions written in each of the years under study.[5]

We then determine the rate of growth in both these sets of measures and whether the relationship between them is direct or inverse—that is, whether states showing greater use of newer medicines are adding to their disability rolls at a greater or lesser rate than states showing a greater use of drugs of older vintage. The nationwide pattern that emerges can inform policymakers about the general effectiveness of newer drugs compared with older ones in reducing disability. Their effectiveness is, of course, only one factor to consider in determining whether alternative or complementary health strategies—such as disease prevention or comprehensive disease management—might be able to reduce total health-care costs even further.

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. They require 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 depend on work history, while the size of DI benefits does reflect one's earnings history and is 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 that we will study: between 1995 and 2004, it increased by 30%, from 2.6% to 3.4%. In an earlier study, Autor and Duggan (2003) developed a theoretical model to try to explain the rise 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;[6] and labor market conditions. They tested some implications of their theory by estimating equations using longitudinal state-level data for 1978–98. These equations included indicators of program generosity and labor market conditions. They found that the combined effect of more generous programs and worsening labor market conditions facing low-skilled workers explained most of the rise in the DI recipiency rate.

Although their theoretical model implies that disability recipiency depends partly on health status, their empirical model 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."

We think that there are good reasons to doubt this claim. As discussed in Lichtenberg (2007), even if the distribution of disease incidence across states were stable over time, different rates of medical innovation directed at 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; education can account for little, if any, of that variation.

This study extends Autor and Duggan's empirical analysis by including hypothesized determinants of health, including indicators of medical innovation, in models of the DI recipiency rate. We perform an econometric analysis of the effect of states' rates of adoption of pharmaceutical innovations, as measured by the change in the mean vintage of all prescriptions written by physicians in the years under study, on the DI recipiency rate, controlling for other possible determinants of health such as age, education, and behavioral risk factors as well as for factors unrelated to health such as DI program generosity and labor market conditions that previous investigators have identified as important influences on DI participation.

We will use data on all outpatient prescription drugs paid for by state Medicaid agencies. Medicaid pays for one in seven U.S. prescriptions. We have data on virtually all the approximately 4 billion Medicaid prescriptions dispensed from 1995 to 2004, by product,[7] state, and year. Since people with less education and fewer skills are most at risk of enrolling in the DI program, drugs used by the Medicaid population might be more relevant to disability 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,[8] and 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%).

All the equations estimated in our study indicate that there is a significant inverse relationship between disability recipiency and a good indicator of pharmaceutical innovation use: drug vintage (the year that a drug's active ingredients were first approved by the FDA). In other words, increased use of newer medicines has reduced the increase in the rate of disability recipiency. 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 it is 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 moved closer to the present in age—that is, if people used the same vintage of drugs in 2004 that 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 by about 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 by about 39%, from 2.62% to 3.65%. This means that, if after 1995, drug vintage had not become more recent, 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.

Although doing so is not a prime purpose of our study, we also offer explanations for interstate variation in the growth in Medicaid drug vintage (i.e., why some states seem to utilize a greater number of newer medicines). Some evidence indicates that those state governments that are among the less financially constrained—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 AIDS incidence: states whose AIDS incidence fell more slowly than average also used a greater number of older drugs in their Medicaid programs. 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. In fact, it is possible that high AIDS incidence may have increased disability rates among patients with other conditions by, in effect, restricting their access to newer treatments.

In light of our findings, policymakers should consider strategies to increase access to newer medical innovations as well as strategies to prevent chronic diseases whose etiology has a strong behavioral component. As we note in our findings on HIV rates, lifelong treatment of newly infected patients with antiretroviral drugs—although lifesaving and highly cost-effective—is more expensive than prevention and may crowd out spending on new medicines in other therapeutic areas. This finding has also been noted recently in international research on AIDS treatment in Africa, where antiretroviral treatment may be crowding out funding of other pressing health-care priorities. The lesson for policymakers is that to maximize the return on investments in health care, the relative merits of long-term treatment, short-term treatment, and prevention strategies must be carefully weighed.

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:

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

N_DISAB_{st} = the number of workers receiving DI benefits in state s in year t (t = 1995, …, 2004)

$POP20\_64_{st}$ = the working-age (aged 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 (aged 20–64) population in state s in year t

$HS\_GRAD\ percent_{st}$ = the percentage of adults who had a high school diploma or higher level of education in state s in year t

$COLLEGE\_GRAD\ percent_{st}$ = the percentage of adults who had a college diploma or higher level of education in state s in year t

BMI_GT25 percent$_{st}$ = the percentage of adults who were overweight or obese (body mass index > 25) in state s in year t

SMOKING percent$_{st}$ = the percentage of adults who smoked in state s in year t

AIDS$_{st}$ = the number of AIDS 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.[10] Since the model includes state and year fixed effects, it is a difference-in-differences model. Negative and significant estimates 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*," or the ratio of DI benefits to previous earnings (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 (1992) 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:

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

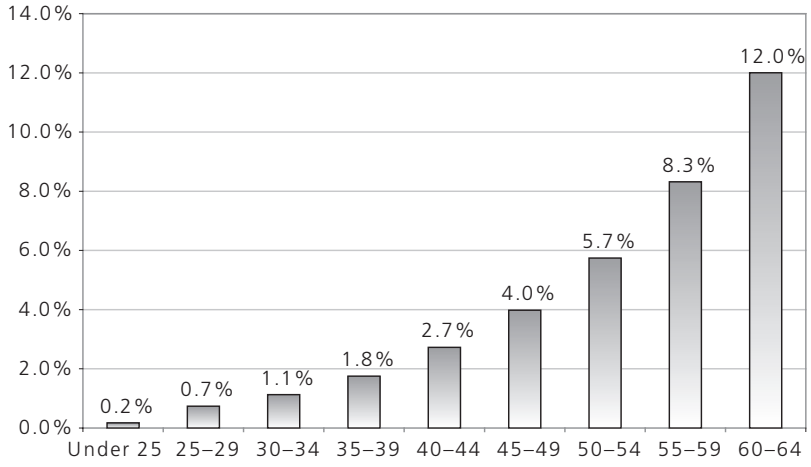
where

EMPi,s,1995 = employment in industry i in state s in 1995

EMPi,US,t = employment in industry i in the U.S. in year t

EMPi,US,1995 = employment in industry i in the U.S. in 1995

Figure I. Disabled Workers as % of Population, by Age, 2006



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 were fixed in the short term. Accordingly, states with a relatively large share of workers in declining industries could be expected to suffer employment declines, while those states employing workers in growing industries could be expected to enjoy 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 people who are more educated are healthier, *ceteris paribus*. For both reasons, an increase in educational attainment is expected to reduce the DI recipiency rate.

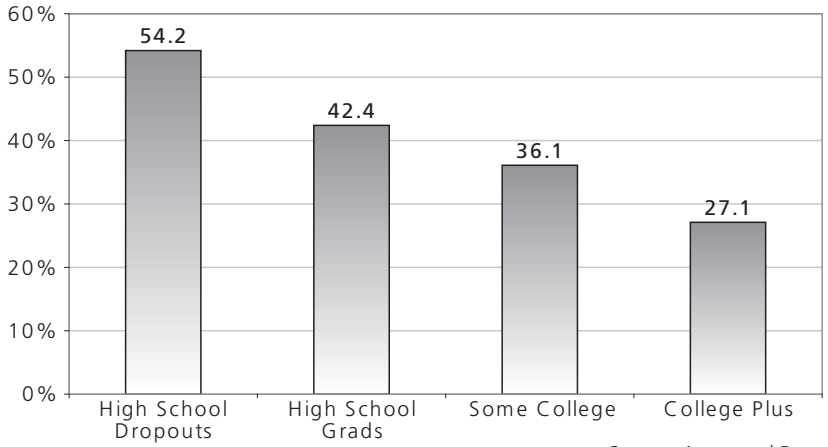
Behavioral risk factors. High BMI (body mass index), smoking, and HIV/AIDS infection are generally considered to be risk factors that reduce health status. Lichtenberg (2007) found that changes in life expectancy were inversely correlated across states with changes in all three of these variables for 1991–2004.

3. MEASUREMENT OF DRUG VINTAGE

All our measures of drug vintage will be based on a combination of data on the utilization of outpatient drugs paid for by state Medicaid agencies and 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 one-seventh of all U.S. outpatient prescriptions in 2004. We have data on virtually all the approximately 4 billion Medicaid prescriptions dispensed from 1995 to 2004, by product, rate, and year. Table 1 shows the distribution of these prescriptions by therapeutic group, as defined in RED BOOK Drug References.[11] There are thirty 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 below-average levels of education and skills are most likely to enroll in the DI program, drugs used by the Medicaid population might have

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



Source: Autor and Duggan

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**	

a greater impact on disability 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,[12] and MEPS data indicate that the fraction of 2004 Medicaid prescriptions that was used to treat mental disorders (12.1%) was 64% higher than the fraction of 2004 non-Medicaid prescriptions that was used to treat mental disorders (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.[13] Lichtenberg (2007) presented evidence that, in six important classes of drugs,[14] 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 prescriptions

tended to increase more in states with larger increases in the vintage of Medicaid prescriptions. 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." The same physicians write prescriptions for both Medicaid and non-Medicaid patients.

We will use four different measures of drug vintage. The first two are based on the following measure of mean utilization-weighted average FDA approval year of the active ingredient,[15] by therapeutic group, state, and year:

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

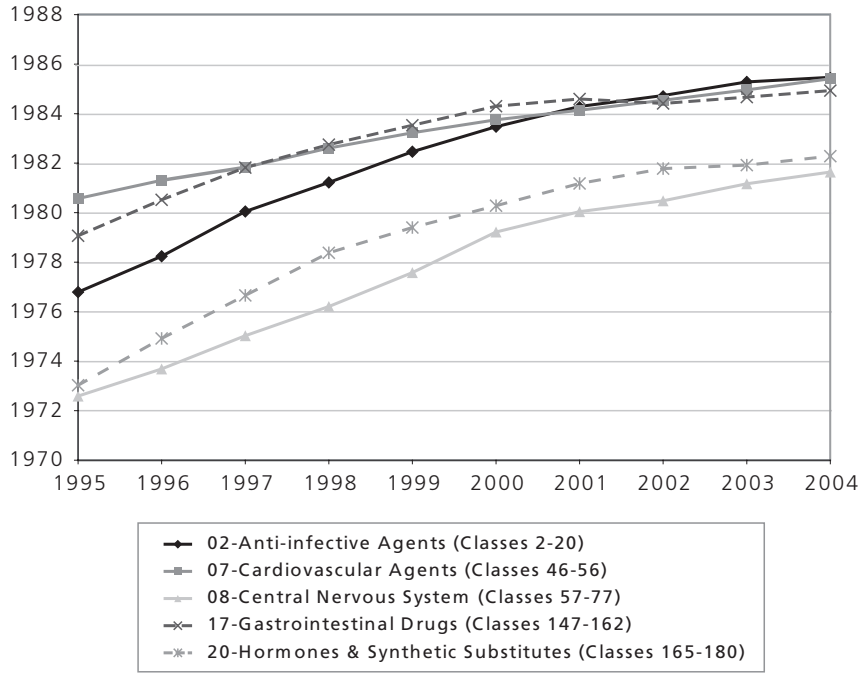
RX_YEARgst = the utilization-weighted average FDA approval year of the active ingredients contained in Medicaid prescriptions in therapeutic group g in state s in year t

N_RXpgst = the number of Medicaid prescriptions for drug product p in therapeutic group g in state s in year t

FDA_YEARp = the year in which the FDA first approved the active ingredient of product p

This calculation yields thirty 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 a rapidly increasing vintage for some therapeutic groups tend to have rapidly increasing vintages for other thera-

Figure 3. Mean Vintage of Five Largest Therapeutic Groups of Medicaid Prescriptions, 1995–2004



peutic 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 measure is simply the weighted average of the therapeutic-group-specific vintage measures, weighted by the number of prescriptions in the therapeutic group:

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

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

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 ten years less recent than the mean vintage of cardiovascular drugs. If the number of cardiovascular prescriptions increased faster than the number of CNS drugs, RX_YEAR_{st} would 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:

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

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

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 constant utilization weights, based on the extent of utilization of drugs within the state from 1995 to 2004. Not counting the effect of changes in the mix of drugs consumed may not be appropriate—changes in disability status may depend on between-therapeutic-group as well as on within-therapeutic group changes in drug vintage—but determining the effect on our estimates of doing so is of interest.

The next two vintage measures that 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 drugs approved before then, so examining the effect of recently approved drugs seems worthwhile.

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

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

$RX\_POST1990\ percent_{gst}$ = 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:

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

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

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

Autor and Duggan (2003) argued that the rise in DI recipiency was partly due to an increase in DI

program generosity over time, including an increase in the probability that a person with a 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: when the latter goes up, the former also goes up. 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 toward 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."[17] 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,

$V^*_d = V_d — STD_d \, \Delta_d$

V^*_d = the effective vintage of drug d
V_d = the actual vintage of drug d
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 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, for simplicity's sake, suppose 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
$V^* = V — STD \text{ percent } \Delta$

STD percent = 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

$$HEALTH = \beta \, V — (\beta \, \Delta) \, STD \text{ percent} + \text{other variables}$$
$$= \beta \, V + \gamma \, STD \text{ percent} + \text{other variables} \quad (8)$$

$$\gamma = - (\beta \, \Delta)$$

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 $STD \text{ percent}_{st}$: the fraction of all prescriptions that in state s in year t were for standard-review drugs.

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 toward zero. Lichtenberg (2008) provided some evidence about the sign of the correlation between pharmaceutical and non-pharmaceutical cardiovascular disease across states.[18] 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 toward zero than away from zero.[19]

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 by about 30% between 1995 and 2004, from 2.6% to 3.4%. The mean values of RX_YEAR and RX_YEAR_WITHIN both increased by about seven 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 rates declined slightly, the fraction of the population that was overweight or obese increased by 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 considering which, if any, of these factors, such as BMI, age, and education level, are associated with drug vintage.[20] 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

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

Dependent Variable	RX_YEAR	RX_YEAR _WITHIN	RX_POST 1990%	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).

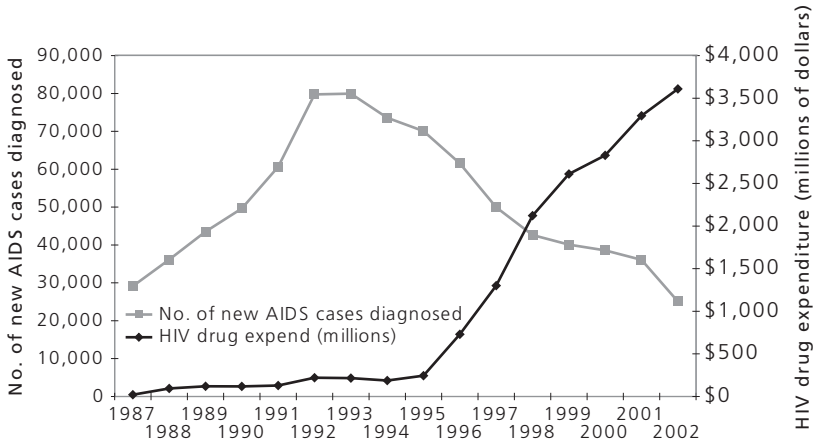
to be more expensive than old drugs, it is plausible that states with lower growth in per-capita tax revenue would have smaller increases in the mean Medicaid drug-vintage or approval year (due, for example, to the adoption of more restrictive formularies).

The dependent variable in column 1 is RX_YEAR, the mean year in which the FDA initially approved 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 where 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 the mean year in which the FDA initially approved a given drug. 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 those state governments that are less financially constrained than the median state 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 AIDS is a comparatively new disease and the treatments for it were approved as recently as the mid-nineties. However, high AIDS incidence may have imposed a substantial burden on the Medicaid budgets of some states, with consequences for the vintage of drugs prescribed for other diseases. 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 for 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. In other words, states with large numbers of AIDS patients dispense prescriptions of older vintage, and that may reflect the efforts of those states to control costs by favoring older drugs for other diseases.

Lichtenberg (2006b) and Duggan and Evans (2008) both provide evidence that part of the increase in drug costs was offset by a reduction in inpatient costs resulting from the 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 may have

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

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

We estimate the effect of pharmaceutical innovation on the DI recipiency rate using longitudinal state-level data and controlling for DI program generosity, labor market conditions, age, education, and behavioral risk factors. 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 prescription patterns of more recent 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.[21] The coefficients on the three behavioral risk-factor variables (SMOKING percent, BMI_GT25 percent, and AIDS) have the expected positive signs, but none is statistically significant.[22] 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 percent (the percentage of adults who had a high school diploma or higher level of education) is not significant, but the coefficient on COLLEGE_GRAD percent (the percentage 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 percentage—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 that allowed us to derive eq. (8): that the difference between the FDA approval year of any standard-review drug and the FDA approval year of the earliest drug with similar therapeutic qualities was the same.

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.[23] In column 5, the drug-vintage measure is RX_POST1990 percent: 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—regardless of the precise definition of drug vintage—there is a significant inverse relationship between disability recipiency and Medicaid drug vintage.[24] Disability recipiency is also consistently inversely related to the average wage rate

Table 4. Estimates of Eq. (I), Model of Disability Recipiency

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).

and COLLEGE_GRAD percent, 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 became more recent 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—that is, if people used the same drugs in 2004 that 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 percent, or RX_POST1990 percent_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.

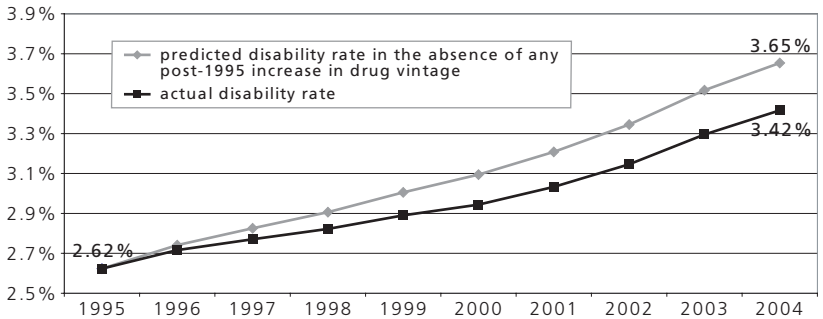
From 1995 to 2004, the actual disability rate increased by about 30%, from 2.62% to 3.42%. The estimates in Table 4 imply that in the absence of any post-1995 increase in drug vintage, the increase in the disability rate would have been 30% larger, and the disability rate would have increased by about 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.[25] In December 2004, the average monthly benefit for disabled workers was $894.10.[26] 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 reduce disability. One study 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 for 1995–2004. The

Figure 5. Predicted Disability Rate in Year t (t = 1996,…,2004), in the Absence of Any Post-1995 Increase in Drug Vintage



disability measure that 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 rates using longitudinal state-level data for 1978–98, 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 using pharmaceutical innovations 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 is its incorporation of drug-vintage measures in models of DI recipiency. All 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 one in seven U.S. prescriptions.

We estimated models of the DI recipiency rate using alternative measures of drug vintage. The implications of all the models were virtually identical. In every case—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—that is, if people used the same drugs in 2004 that 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 by about 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 by about 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 state governments that were less financially constrained—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 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 the states exhibiting those rates to restrict, for budgetary reasons, their residents' access to newer treatments.

Appendix Table I. 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%	hs_gradcollege_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%

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%	hs_gradcollege_grad%
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%
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

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Endnotes

1. 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 toward zero. Lichtenberg (2008) provided evidence about the sign of the correlation between pharmaceutical and non-pharmaceutical cardiovascular disease innovation across states.

2. 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.

3. 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, 2007, and 2008).

4. We will refer to this ratio as the DI recipiency rate.

5. The dictionary contains several different definitions of vintage. The definition we use is: "a period of origin or manufacture." We define the vintage of a drug as the year in which the U.S. Food and Drug Administration (FDA) first approved the drug's active ingredient. For example, the vintage of all products (branded and generic) containing simvastatin is 1991, the year this active ingredient was first approved by the FDA. Use of newer drugs results in an "increase" in drug vintage.

6. 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.

7. There are currently about 46,000 products.

8. See http://ssa.gov/policy/docs/statcomps/di_asr/2006/table21.xls.

9. 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.

10. Since N_DISABst / POPst is bounded between zero and one, a linear model would not be appropriate.

11. See http://www.micromedex.com/products/redbook. Therapeutic group is an aggregation of therapeutic class values.

12. See http://ssa.gov/policy/docs/statcomps/di_asr/2006/table21.xls.

13. 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 September 2004–December 2006.

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

15. 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.

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

17. See http://www.fda.gov/Cder/rdmt/InternetNME08.htm.

18. The measure of non-pharmaceutical innovation in the treatment of cardiovascular disease that he used was the fraction of Medicare major cardiovascular surgical procedures that were given procedure codes by the American Medical Association after 1990 or 1995.

19. Lichtenberg (2007) found that controlling for a measure of *nonmedical* 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.

20. 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).

21. 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.

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

23. In column 4, STD percent is replaced by STD percent_WITHIN.

24. 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 have a positive effect on life expectancy (at birth and at age sixty-five). But the effect of Medicare drug vintage on disability in the working-age population is not statistically significant.

25. 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 percent	431,525
rx_post1990 percent_within	467,009

26. See http://ssa.gov/policy/docs/statcomps/di_asr/2004/sect01c.html#table20.

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The Center for Medical Progress (CMP) is dedicated to articulating the importance of medical progress and the connection between free-market institutions and making medical progress both possible and widely available throughout the world. The research and writing of CMP senior fellows David Gratzer, Regina Herzlinger, Paul Howard, Peter Huber, and Benjamin Zycher encourage the development of market-based policy alternatives to sustain medical progress and promote medical innovation.

CMP fellows are published in prominent publications such as the *Wall Street Journal*, the *Washington Post*, *National Review*, and the *Weekly Standard*. In 2006 and 2007, Gratzer and Herzlinger each released a book examining health care in the United States. Gratzer's *The Cure: How Capitalism Can Save American Health Care* received nationwide acclaim, leading the *Wall Street Journal* to recommend that "our nation's policy makers read *The Cure*" and prompting the *Washington Post* to describe Gratzer's work as "an artful job of concisely laying out what ails the U.S. system and how things got to be that way."

Herzlinger, the Nancy R. McPherson Professor of Business Administration Chair at the Harvard Business School, is widely recognized throughout the business and policy communities for her innovative research in health care. Her newest book, *Who Killed Health Care?: America's $2 Trillion Medical Problem—and the Consumer-Driven Cure*, exposes the motives and methods of those who have crippled America's health-care system. Zycher is researching the economic and political effects of regulation, government spending, taxation, and the economics of the pharmaceutical sector.

In 2005, CMP established the 21st Century FDA Task Force to devise and promote better science-based regulations at the FDA that will decrease the time and cost required for new drug development while increasing the safety and efficacy of the nation's drug supply. The Task Force is composed of experts from academia, industry, and the policy community, and will develop and disseminate proposals to reform the FDA's drug approval and safety monitoring procedures.

CMP also publishes MedicalProgressToday.com, a blog that provides a daily commentary of the best published research and analysis of health-care issues from a free-market perspective. In addition, MPT solicits original spotlight op-eds on critical health-care topics, and convenes policy forums where leading scholars exchange views on important health-care issues. Contributors to MPT have included Richard Epstein, Newt Gingrich, Scott Gottlieb, and J. Edward Hill.