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An Empirical Method For Measuring The Restrictiveness Of State Medicaid Programs

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QUANTIFYING THE RESTRICTIVENESS OF MEDICAID ELIGIBILITY POLICY

Abstract

Objective. Our objective is to construct a quantitative summary measure of the restrictiveness of state-level Medicaid eligibility policy. This measure is useful in interstate comparisons and individual-level statistical models of Medicaid enrollment.

Data Sources. State-year-level data are collected from several sources including the Centers for Medicare and Medicaid Services, the Bureau of Labor Statistics, and the Kaiser Family Foundation. Individual-level data are extracted from Medicare and Medicaid claims and from the Department of Veterans Affairs.

Study Design. This is a retrospective analysis of secondary data. We estimate a fixed effects regression model predicting the proportion of state population enrolled in Medicaid as a function of economic variables. We use the estimated state effects as identifying instruments in an individual-level model of Medicaid enrollment.

Data Collection. Only secondary data are used.

Principal Findings. The fixed effects model fits the data very well, explaining 49 percent of within-state variation in Medicaid enrollment. The estimated Medicaid restrictiveness variable is very powerful in the individual-level model, producing a marginal effect larger than any other variable except indicators for AIDS and psychosis.

Conclusions. The restrictiveness of Medicaid eligibility policy can be usefully summarized using a relatively simple regression model and widely available data.

Objective

Medicaid is a federally mandated health care program for children, parents of children, and certain disabled, elderly and working individuals. The federal government mandates minimum eligibility standards and benefit levels to be provided by the states. States are permitted the option to exceed the minimum standards so that they may provide services to more people as well as the option to provide additional services so that more comprehensive care may be provided. This flexibility has effectively resulted in fifty different state-level Medicaid programs.

Health care researchers have often been interested in investigating the effects of differences in state Medicaid policies on state level enrollment, quality of care, health outcomes, utilization and costs. In conducting this research across states, investigators have generally chosen to study one aspect of Medicaid policy as it affects a narrowly defined outcome.

Examples of this type of research include studies of the effects of: nursing home reimbursement rates on hospitalization of patients (Intrator, Mor 2004); Medicaid program characteristics on the use of Medicare home health care (Cohen, Tumlinson 1997; Kenney, Rajan 2000); nursing home reimbursement rates on enrollment into nursing homes (Hoerger, Picone and Sloan 1996); psychiatric drug formularies on health outcomes of mental health patients (Cuellar, Markowitz 2007); and Medicaid eligibility levels on hospital care for AIDS patients (Andrulis et al. 1987).

Other research has attempted to characterize differences among states by using various classification schemes or typologies (Trenholm, Kung 2000; Rajan 1998; Holohan, Pohl 2002; Spillman 2000). Descriptive factors are used to classify and rank

states into categories. Among the factors considered are eligibility thresholds, waivers obtained by the state that indicate the state exceeds minimum federal requirements, asset and income thresholds for nursing home and home health patients, the federal matching rate, and the existence of supplemental health programs funded only by the state. Generally, typologies classify states into one of three or four categories on scales that may be labeled "most generous to least generous" or "most innovative to least innovative."

Research focusing on the impact of specific Medicaid policies is invaluable in its contribution to understanding how state to state differences in policies may lead to enrollment variation among states. Similarly, the development of typologies that classify states into qualitative categories of generosity or innovation can be very useful for descriptive work. These approaches are insufficient, though, if the research goal is to quantify the general restrictiveness of Medicaid eligibility policy across states or to assess the effect of Medicaid enrollment on specific outcomes. These goals go together because Medicaid enrollment is typically jointly determined with specific outcomes, so estimating the effect of Medicaid enrollment on outcomes requires statistical techniques that explicitly model the probability of Medicaid enrollment in one equation and use a second equation for the outcome.

A principal challenge with these techniques is to find variables that identify the Medicaid enrollment equation as a function distinct from the outcome equation. In other words, the researcher needs variables that ought to affect the probability of Medicaid enrollment directly, but have no effect on the outcome variable except for the indirect effect through Medicaid enrollment. Medicaid eligibility policy variables are perfect for

this purpose. In this article, our objective is to use an easily reproduced state-level enrollment regression to generate an overall measure of Medicaid eligibility restrictiveness that is informative on its own and also useful for identifying individual-level studies of the effect of Medicaid enrollment on health outcomes.

Methods and Data: State-level Model

The proportion of the population enrolled in Medicaid varies substantially from state to state. This proportion, unadjusted, could be used in individual-level models of Medicaid enrollment and interpreted as a measure of the restrictiveness of eligibility policy. This would be a rough approximation, however, because some of the variation from state to state is certainly due to differences in the demand for Medicaid coverage, not differences in policy. Holding eligibility policy and benefits constant, demand for Medicaid is likely to be affected by labor market conditions, including income levels, levels of unemployment, and the availability of health insurance coverage from employers. Our goal with the state-level model is to adjust state-level variations in Medicaid enrollment to remove the effects of demand fluctuations, leaving variation that is attributable to differences in Medicaid policy.

We begin by identifying characteristics of the state population that might affect demand for Medicaid coverage, particularly if they also might be correlated with potential health outcomes of interest (like mortality, hospitalization, or functional status). Because Medicaid eligibility in all states is a function of income, we include in our model per capita income and the poverty rate for those aged 18-64. In addition, individuals will be more likely to apply for Medicaid coverage if they have no other source of insurance, so we control for the unemployment rate and the percent of the population with

employer-sponsored insurance. All of these variables are readily available for each state and measured in nearly every year. After removing the effects of these demand factors, we believe that most of the remaining variation in Medicaid enrollment is due to differences in the benefits and eligibility rules that govern each state program. As a group, these policy variables are more stable through time than the demand variables, although some changes certainly occur each year. These policy variables are also more difficult to measure and less accessible to researchers in consistent form over time. For these reasons, we obtain consistent estimates of the effects of the demand variables by consolidating the effects of state-level policy differences on enrollment into a state-level time-invariant effect. This effect will account for the impact of Medicaid policy differences that are constant through time as well as state-only insurance programs and other time-invariant demographic, economic, and financial characteristics that are not otherwise captured by the model. The model can be expressed as:

$$pMcaid_{st} = \beta_1 income_{st} + \beta_2 \%covered_{st} + \beta_3 poverty_{st} + \beta_4 unemp_{st} + \delta_s + \varepsilon_{st}$$

where the subscripts s and t index states and years, respectively. In the equation, $\beta_1 - \beta_4$ denote coefficients to be estimated, δ represents the state-level effect, and ε is the regression residual.

Dependent variable

The dependent variable in the model is the proportion of the overall state population enrolled in the Medicaid program (denoted pMcaid in the equation). This was obtained from the HCFE State-Level Medicaid Dataset (Frakt 2005) which was developed using publicly available data from the Centers for Medicaid and Medicare Services. To arrive at the proportion of the population enrolled in Medicaid we divided

the number of state residents enrolled in Medicaid for at least 1 month during the year by each state's total population.

Independent variables

The independent variables are four socio-demographic variables related to the demand for services. These are per capita income, the poverty rate for those aged 18-64, the percentage of people covered by employer-sponsored insurance, and the unemployment rate. Per capita income for years 1998-2002 is from the Bureau of Economic Analysis (BEA) website http://www.bea.gov/bea/regional/spi/. Per capita income is total personal income divided by total midyear population. Total midyear population estimates are taken by BEA from the Bureau of the Census. The poverty rate data for ages 18-64 are from the Current Population Survey (CPS) Annual Demographic Survey - March Supplement for years 1998-2002. Weighted person count tables were used.

The percentage of the population with employer-sponsored insurance was obtained from the Kaiser Family Foundation (KFF) statehealthfacts.org project website and archived files provided to the authors by KFF. Data for this variable was available for all years 1998-2002 with the exception of 1999. Based upon available data, we interpolated the data for each state for 1999. The unemployment rate data is from a variety of sources. The 1998 data is from the Geographic Profile of Employment and Unemployment - Table 16. Data for 1999-2003 is from the U.S. Bureau of Labor Statistics website (http://www.bls.gov/lau/home.htm). Data for 1999 was taken from the section titled "Over the Year Change in Unemployment Rates for States" and 2000-2003 data was taken from the section titled "Unemployment Rates for States." The

unemployment rate data exclude persons with no previous work experience. The data collected covered the years 1998 to 2002 for all 50 states. Table 1 lists the variables, their sources, and means over 5 years.

Specification of state-level effect

The state-level effect (δ in the equation) could be estimated as a fixed effect or a random effect. If a random effects specification is appropriate (also known as a multi-level model), a variety of distributional assumptions can be tried to achieve the best fit. The suitability of a random effects model depends on whether the state effects are correlated with any of the other independent variables. If they are, all the coefficient estimates will be biased. Because a fixed effects specification will be unbiased regardless of this kind of correlation, a Hausman test that compares coefficients from fixed and random effects specifications can be used to determine which one to use (Hausman 1978).

Methods and Data: Individual-level Model

To illustrate the value of the state policy effects estimated with the state-level model, we consider the selection bias problem that may arise when a researcher wishes to use observational data to estimate the effects of program participation on outcomes. Are observed and unobserved factors that influence the outcome also correlated with selection into or out of the program? If so, the estimated effect of program participation could be seriously biased. Statistical techniques for addressing this problem include propensity score matching, simultaneous equations, and instrumental variables (see Ichimura and Taber 2001 for a brief overview). All of these methods require as a first step that an individual-level model of program participation be estimated. Typically, a logistic

regression or a probit model is used to relate individual enrollment to socio-economic and health status variables. To distinguish (identify) this enrollment model from the outcome model, it is necessary to have variables that ought to affect enrollment without directly affecting the outcome. Finding such variables can be a challenge. We use an example to demonstrate that the state policy effects estimated above can serve this purpose very well.

Simultaneous enrollment in multiple health care financing programs might improve outcomes by helping to finance a more comprehensive set of services, or it might compromise quality by making coordination of care more difficult. As researchers situated within the Veterans Health Administration (VA) we have access to individual-level data for veterans who use the VA, some of whom also use services financed by Medicaid. If we simply compare outcomes for dually enrolled veterans with outcomes for those relying exclusively on the VA, we find that the dually enrolled fare poorly. This is mostly due to the fact that dually enrolled veterans are in worse health, as reflected by diagnostic codes. But the contrast in outcomes persists even if we use a regression model to control for all observable differences in health status. Because Medicaid programs grant eligibility to some individuals on the basis of acute need for health care services, it is likely that unmeasured differences in health status exist between dually and singly enrolled groups and that these differences are correlated with outcomes. To begin to address this problem we have estimated an individual-level probit model to predict the probability of Medicaid enrollment as a function of individual characteristics, VA program characteristics, and Medicaid restrictiveness as estimated above. The results of this model could be used to construct propensity scores for improved matching or as the first stage of an instrumental variables or simultaneous equations specification.

We selected a representative sample of VA patients drawn from the VA national patient care database. Starting with all veterans who used VA services from October 1, 1997 to September 30, 2001 (federal fiscal years 1998 to 2001), we sampled 10% of those with any Medicaid enrollment in 1999 or 2000 and 3% of all others. We excluded Priority 7 or 8 veterans from the sample because the VA means test determined that their incomes were relatively high, implying that they would not qualify for Medicaid. We also excluded those with missing priority status or means test values. We focused our Medicaid enrollment model on the first six months of 2000 and the final sample included 22,629 veterans who had some Medicaid enrollment in that period and 49,330 who did not.

The independent variables in this individual-level model include: distance from a VA medical center; distance from a VA outpatient clinic; state policy effects (restrictiveness); the veteran's priority level, gender, and age; and the percentage of the population in the veteran's Zip Code who are nonwhite. The distance variables are calculated as the distance from mid-point to mid-point of the VA facility Zip Code and the Zip Code of residence for the veteran.

Additionally, indicator variables for 30 co-morbidities developed by Elixhauser (Elixhauser et al. 1998) are included as risk adjustment measures. These co-morbidities include a wide variety of physical and mental conditions such as diabetes, neurological disorders, chronic pulmonary disease, depression, alcohol abuse, and drug abuse. To construct these variables we extracted diagnosis codes from all inpatient and outpatient encounters financed by VA, Medicare, or Medicaid for our sample of veterans in 1999.

Although numerous studies have validated these data for particular purposes (Fleming et al. 1992; Kashner 1998; Goldstein 1998; Szeto et al. 2002; Kiyota et al. 2004), the limitations of administrative data are well known (Iezzoni 1997). Coding practices vary somewhat from hospital to hospital and from clinic to clinic. After a particular encounter, acute conditions directly related to the reason for the encounter are more likely to be coded than chronic conditions that were not treated at the time. Most challenging for our analysis, financial incentives differ between VA and non-VA institutions with non-VA payment depending on coding. We hope to minimize the effects of coding inconsistencies by grouping codes into relatively broad categories and by collecting codes over a relatively long period of time (one year prior to our study period), but caution is nevertheless warranted when interpreting results.

State policy effects can be included in the model in two ways. First, the estimated state fixed effects (δ_s in the equation) could be used to measure the average restrictiveness of Medicaid policy over several years. Alternatively, the full residual from the state-level regression ($\delta_s + \varepsilon_{st}$ in the equation) could be used to reflect both permanent and transitory policy differences. The latter approach is equivalent to using the annual Medicaid enrollment rate, adjusted for fluctuations in measurable demand variables. This formulation will be more powerful in the individual-level model, but it may be less easily interpreted as a measure of policy differences.

Findings

State-level model hypotheses

We expect higher per capita income and a higher rate of employer-sponsored health insurance coverage to be associated with a lower proportion of the population

enrolled in the Medicaid program. Higher poverty and unemployment rates should be associated with higher enrollment proportions. The state effects will capture time-invariant differences in Medicaid enrollment that are not predicted by differences in income, insurance availability, poverty rates, or unemployment rates. These ought to reflect differences in state Medicaid and state health policy that affect the probability of enrollment into that state's Medicaid program. Positive values will indicate more generous policies leading to a positive effect on enrollment, and negative values will indicate more restrictive policies leading to a negative effect on enrollment.

State-level model results

Estimated coefficients for each of the independent variables produced by a fixed effects model are reported in Table 2. Three variables - per capita income, the percentage of people covered by employer-sponsored insurance, and the unemployment rate had statistically significant effects at the $p < 0.01$ level. The effect of the poverty rate for those aged 18-64 was significant at $p = 0.02$. Three out of four coefficients indicate effects in the expected direction. As expected, the percentage of people covered by employer-sponsored insurance is negatively associated with the proportion of the population enrolling in Medicaid. Also as expected, as poverty levels and unemployment rates increase the proportion of the population enrolled increases. In contrast, as per capita income increases, the proportion of the population enrolling in the Medicaid program also increases. This is contrary to our expectation. We hypothesized that as per capita income increased individuals would be better able to afford private health insurance and would not be as likely to enroll in a public insurance program. One possible explanation for the unexpected effect of per capita income is that high income

states are also typically high cost states with intensive health care practice patterns. Holding poverty rates constant, states with higher costs and more intensive practice patterns would be expected to have more residents turning to Medicaid for help in paying for care.

We also estimated a random effects model and compared the fixed and random effects results using a Hausman test. The test statistic was 56.2 for a Chi-squared with 4 degrees of freedom (bottom of Table 2), overwhelmingly rejecting the random effects specification. Overall, the fixed effects specification fit the data very well, explaining 49 percent of the within-state variation in the proportion of the population enrolled in Medicaid.

Estimated state effects

As previously described the state effects reflect persistent differences among states that are not explained by the independent variables included in the equation. These state specific, unobservable differences may include a variety of differences in state policy including eligibility levels, services provided, benefits provided, the medically needy threshold, income and assets thresholds for nursing home and home care programs, treatment of two parent working families and of disabled working adults, waivers obtained by the state that indicate the state exceeds minimum federal requirements, the federal matching rate, and the existence of supplemental state only funded health programs. Table 3 shows the estimated state effects for states from 1998 to 2002. The range for all states is -0.13 to +0.14. A positive effect indicates that holding all the independent variables constant the state enrolled more individuals than average. A negative effect indicates that holding all independent variables constant the state enrolled

fewer individuals than average. An effect of zero or near zero indicates that the state enrolled approximately the number of individuals predicted by the independent variables into its Medicaid program.

One might expect that wealthier states would enroll more people than predicted by the independent variables and poorer states would enroll fewer people. What we find when we look at the results is that states we would categorize as among the less wealthy, such as Tennessee and Vermont, actually enroll more individuals than predicted. These states may be said to have more generous policies than average. States such as Massachusetts, Minnesota and New Jersey, perceived to be among the more wealthy states with less unemployment and poverty and higher incomes, actually enroll fewer individuals into their Medicaid programs than predicted. These results may be interesting to researchers and policymakers on their own, and they are also valuable for health outcomes research, as we demonstrate next.

Individual-level model results

For the purposes of this article we are interested in the explanatory variable labeled "restrictiveness" in Table 4. For ease of labeling and interpretation "restrictiveness" refers to the negative of the state policy effects estimated from the state-level model discussed above. The estimated effect of Medicaid policy restrictiveness is negative (-1.29), statistically significant, and indicates that as state policies become more restrictive the probability of enrollment into the Medicaid program decreases for each individual. To evaluate the relative importance of this variable we examine its estimated marginal effect (-0.47), which indicates that a change of 0.1 in restrictiveness would result in a 5% change in probability of enrollment. Another way to appreciate the size of

this effect is to consider the consequences of moving from the most restrictive state to the least restrictive. Such a move would reduce restrictiveness by 0.27, resulting in an increase in enrollment probability of 13 percentage points. This is comparable to the effect of percent nonwhite, which ranges from zero to one. If one moved from a Zip Code with zero percent nonwhite to one with 100 percent nonwhite, the estimated increase in enrollment probability would be 13.2 percentage points. Only two health conditions had greater estimated marginal effects than restrictiveness: AIDS (28 percentage points) and psychosis (18 percentage points).

In general, the other variables in the model had effects that were consistent with expectations. Increasing distance to VA medical centers or outpatient clinics made enrollment in Medicaid more likely. Relatively high priority status for VA services made Medicaid enrollment less likely. Younger veterans, those living in neighborhoods with more nonwhites, and women were more likely to enroll. Most health conditions made Medicaid enrollment more likely. Blood loss anemia, cardiac arrhythmia, lymphoma, and tumor without metastases were exceptions but had small effects.

Of the health conditions, obesity had the largest negative effect on Medicaid enrollment, a counter-intuitive result that could be due to reverse causation. We observe much higher rates of obesity recorded in VA data than in Medicare or Medicaid claims for the same veterans. This implies that obese patients are more likely to have their obesity coded if they receive care from the VA. If this is true, then established VA patients will be more likely than patients who rely more heavily on Medicare- or Medicaid-financed care to be recorded as obese. Obesity, then, does not make Medicaid

enrollment less likely; Medicaid enrollment makes it more likely that obesity will not be observed in the data.

Because we have included state policy effects in our model to predict Medicaid enrollment, we are confident that the estimated effect of Medicaid enrollment in our outcomes models will be strongly identified, making simultaneous equations and instrumental variables techniques feasible.

Conclusion

We demonstrate an easily reproduced method for summarizing the effects of state Medicaid enrollment policy for use in quantitative models. The underlying objective is to develop a measure that can be included as an explanatory variable in person-level models designed to predict the effect of Medicaid enrollment on outcomes. We show by example how the measure can be used and the strength of model identification that results. When used in a person-level model of Medicaid enrollment our constructed measure of Medicaid policy restrictiveness had a highly significant effect that was comparable in size to the effects of chronic pulmonary disease, paralysis, or percent nonwhite in the Zip Code of residence. The only health conditions that had larger effects were AIDS and psychoses.

The particular estimated values of Medicaid policy restrictiveness are also of interest because they constitute a measure of state-by-state access to Medicaid coverage. Some relatively low-income states like Tennessee and Vermont have very accessible Medicaid programs and some higher income states like Connecticut and New Jersey have less accessible programs. This may seem unsurprising because the federal match rate is higher for lower income states, a policy that provides additional federal assistance to

states that are less able to finance their own programs. However, when we included the federal match rate in our models it had minimal explanatory power, suggesting that the observed heterogeneity in access to Medicaid coverage is a result of state, not federal policy. Further research is needed to identify the policy differences most responsible for these patterns.

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Table 1. Variable names, descriptions, sources and means

Variable Name	Variable Description	Source	Mean across states for years 1998 -2002
pMcaid	Proportion of state population enrolled in Medicaid	HCFE State-Level Medicaid Dataset	0.153
income	Per capita income	Bureau of Economic Analysis	27.956
%covered	Percentage covered by employer-sponsored insurance	Kaiser Family Foundation www.statehealthfacts.org and archived files	0.590
poverty	Poverty rate for those aged 18-64	Current Population Survey - Annual Demographic Survey- March Supplement	0.099
unemp	Unemployment rate	U.S. Bureau of Labor Statistics	0.043

Table 2. State-Level Fixed Effects Model: Proportion of Population in Medicaid

Variable	Coefficient	Standard Error	t
Per capita income	0.01***	0.001	8.63
Percent covered by employer insurance	0.08***	0.02	-3.22
Poverty rate (18-64)	0.18**	0.08	2.36
Percent unemployed	0.88***	0.11	7.85
Constant	- 0.12	0.03	-3.62
Number of observations	250		
R-squared within	0.49		
Hausman test statistic	Chi-square (4) = 56.2 ; P < 0.0000		

*** P < 0.01; ** P < 0.05

Table 3. Estimated State Policy Effects, 1998 - 2002

State Abbreviation	Estimated Effect	State Abbreviation	Estimated Effect
AK	-0.016	MT	-0.011
AL	0.043	NC	0.016
AR	0.082	ND	-0.012
AZ	0.014	NE	0.006
CA	0.025	NH	-0.085
CO	-0.092	NJ	-0.131
CT	-0.124	NM	0.093
DE	-0.007	NV	-0.087
FL	-0.015	NY	-0.034
GA	0.018	OH	-0.015
HI	0.005	OK	0.047
IA	-0.005	OR	0.003
ID	-0.003	PA	-0.020
IL	-0.040	RI	0.012
IN	-0.003	SC	0.076
KS	-0.042	SD	0.015
KY	0.054	TN	0.138
LA	0.060	TX	-0.023
MA	-0.050	UT	-0.007
MD	-0.066	VA	-0.060
ME	0.064	VT	0.104
MI	-0.016	WA	-0.030
MN	-0.042	WI	-0.025
MO	0.034	WV	0.081
MS	0.108	WY	-0.038

Table 4. Individual-Level Medicaid Enrollment Model

Variable	Estimate		Standard Error	Marginal Effect
Intercept	-0.591		0.028	
Distance to VA medical center	0.0004	***	0.0001	0.0001
Distance to VA outpatient clinic	0.001	***	0.0003	0.0004
Medicaid Restrictiveness	-1.291	***	0.105	-0.477
Percent nonwhite in Zip Code	0.352	***	0.020	0.132
Age	-0.002	***	0.0004	-0.0008
VA priority status 1 to 3	-0.344	***	0.016	-0.115
VA priority status 5	-0.048	***	0.014	-0.017
Female	0.197	***	0.022	0.072
Aids	0.736	***	0.060	0.284
Alcohol abuse	0.216	***	0.025	0.079
Blood loss anemia	-0.048		0.086	-0.017
Arrhythmias	-0.001		0.025	-0.0004
Congestive heart failure	0.122	***	0.025	0.044
Coagulopathy	0.071		0.048	0.025
Chronic pulmonary disease	0.338	***	0.017	0.125
Deficiency anemias	0.137	***	0.026	0.050
Depression	0.148	***	0.022	0.053
Diabetes	0.085	***	0.016	0.030
Drug abuse	0.222	***	0.031	0.082
Fluid and electrolyte disorders	0.192	***	0.030	0.070
Hypertension	0.100	***	0.013	0.035
Hypothyroidism	0.031		0.037	0.011
Liver disease	0.315	***	0.043	0.117
Lymphoma	-0.012		0.082	-0.004
Metastatic cancer	0.188	***	0.063	0.069
Obesity	-0.062	**	0.030	-0.021
Other neurological disorders	0.315	***	0.027	0.117
Paralysis	0.333	***	0.050	0.125
Pulmonary circulation disorders	0.169	**	0.079	0.062
Peptic ulcer	0.209	***	0.045	0.077
Peripheral vascular disorders	0.121	***	0.025	0.044
Psychoses	0.488	***	0.019	0.184
Renal failure	0.175	***	0.038	0.064
Rheumatoid arthritis	0.083		0.046	0.030
Tumor without metastases	-0.017		0.023	-0.006
Valvular disease	0.017		0.038	0.006
Weight loss	0.155	***	0.063	0.056
Number of observations	71,959			

** $P < 0.05$; *** $P < 0.01$