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RESEARCH ARTICLE

The Impact of Medicare Part D on Hospitalization Rates

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Objective. To determine whether the change in prescription drug insurance coverage associated with Medicare Part D reduced hospitalization rates for conditions sensitive to drug adherence.
Data Sources/Study Setting. Hospital discharge data from 2005 to 2007 for 23 states, linked with state-level data on drug coverage.
Study Design. We use a difference-in-difference-in-differences approach, comparing changes in the probability of hospitalization before and after the introduction of the Part D benefit in 2006, for individuals aged 65 and older (versus individuals aged 60–64) in states with low drug coverage in 2005 (versus those in states with high pre-Part D drug coverage).
Data Collection/Extraction Methods. Hospitalization rates for selected ambulatory care sensitive conditions in 23 states were computed using data from the Census and Health Care Utilization Project. Drug coverage rates were computed using data from several sources.
Principal Findings. For the conditions studied, our point estimates suggest that Part D reduced the overall rate of hospitalization by 20.5 per 10,000 (4.1 percent), representing approximately 42,000 admissions, about half of the reduction in admissions over our study period.
Conclusions. The increase in drug coverage associated with Medicare Part D had positive effects on the health of elderly Americans, which reduced use of nondrug health care resources.

Key Words. Medicare, prescription drugs, hospitalization

The Medicare Part D program, launched in 2006, increased the share of Medicare beneficiaries with prescription drug coverage from 59 to 89 percent (authors' calculation). This expansion of benefits recognizes that prescription drugs are an indispensable component of care management, particularly for chronic disease. The evidence suggests that, even in a narrow time window, better management of certain conditions with prescription drugs can reduce the likelihood of adverse events like hospitalizations and the costs associated with them (Goldman, Joyce, and Zheng 2007; Stuart, Doshi, and Terza 2009).

Thus, because use of prescription medications is related to the generosity of coverage (Goldman et al. 2007), we would expect that the increase in drug coverage resulting from Part D will increase adherence to important medications and lead to improved health and fewer hospitalizations.[1]

Evidence from national data supports the first portion of this argument, that Part D increased prescription drug use (Yin et al. 2008; Schneeweiss et al. 2009). Other research examining the experience of a single insurer suggests that extra spending on medications was offset by reduced spending on other medical services (Zhang et al. 2009). Presumably, a reduction in hospitalizations was a significant component of this offset. The effects could be greatest on admissions for ambulatory care sensitive conditions (Weissman, Gatsonis, and Epstein 1992; Bindman et al. 1995).

Examination of hospitalization is also important because it can help assess the clinical impact of Part D. Specifically, because Part D did not affect incentives for hospitalization, any changes in hospitalizations related to Part D-induced changes in drug coverage are likely due to changes in underlying health status. By assessing the impact of Part D on hospitalizations, we can gain insight about the effects of this policy change on health more generally.

Existing research has not examined the impact of Part D on hospitalization (or any markers of health outcomes) directly. In part, this is because linked data on drug coverage, drug utilization, and outcomes are not available. We surmount this problem by conducting an area level study. Our analytic strategy uses the fact that drug coverage was more prevalent in some geographic areas than in others before Part D. Thus, some states were more affected by Part D than others. We assess whether the states most affected by Part D had greater changes in admissions for diagnoses potentially amenable to drug coverage, compared with states less affected by Part D. We control for unobserved state trends by examining admission rate changes in the same states over the same study period for individuals aged 60–64, who for the most part did not see their drug coverage change with the introduction of Part D. This study design is analogous to an intention to treat analysis and therefore addresses the issue of nonrandom selection into Part D plans by examining market-level effects.

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METHODS

Data Sources

We use data from several sources. First, we calculate rates of hospitalizations for our eight conditions using counts of admissions inpatient data and estimates of the population from the census. The data on admissions are taken from the Agency for Healthcare Research and Quality's (AHRQ) Health Care Utilization Project (HCUP). Among the HCUP databases is the Statewide Inpatient Database (SID), which contains discharge data from nearly all hospitalizations in several states. We utilize SID data from the 23 states for which we were able to procure data from AHRQ using simplified request procedures, and for which records were available for the period 2005–2007: Arizona, Arkansas, California, Colorado, Florida, Hawaii, Iowa, Kentucky, Maryland, Michigan, Nebraska, Nevada, New Jersey, New York, North Carolina, Oregon, Rhode Island, South Carolina, Utah, Vermont, Washington State, West Virginia, and Wisconsin. Of the approximately 37 M individuals aged 65 and older in 2005, more than half (20 M) resided in these states.

Using the SID files for these states, we count hospitalizations separately by state, year, and two age groups: 60–64 and 65-plus. We count the number of hospitalizations for eight conditions that we expect to be sensitive to drug adherence: short-term complications of diabetes, chronic obstructive pulmonary disorder, congestive heart failure (CHF), angina, uncontrolled diabetes, asthma, stroke, and acute myocardial infarction (AMI). A description of the ICD-9-CM diagnosis codes used to identify each hospitalization is available in an appendix. As a summary measure, we count the number of hospitalizations for any of these eight conditions.

We compute a denominator for each condition using data from the United States Census and calculate the condition-specific hospitalization rate. The denominator is comprised of the entire population for each state-and-year-specific age group. Because the vast majority of individuals 65-plus are covered by Medicare, these population estimates are a very close approximation of the true denominator.

For the same time period, we generate state-level drug coverage estimates for individuals aged 65 and older. We use data on nine types of drug coverage among Medicare beneficiaries: stand-alone Medicare Part D plans, Medicare Advantage Part D plans, beneficiaries dually enrolled in Medicaid, employer-sponsored retiree coverage (ESR), Federal Employees Health Benefits Plan and Tricare coverage, Veteran's Administration coverage, Indian

Health Service coverage, active workers, and state pharmaceutical assistance programs (SPAP). In an appendix, we describe how we derive our estimates for each of these coverage categories.

We do not have comparable drug coverage data for individuals aged 60–64. We make the assumption that any change in the coverage rate for this age group between 2005 and 2006 was not systematically related to Part D-induced state-level changes in coverage for Medicare beneficiaries. Estimates from the Census Bureau's Small Area Health Insurance Estimates (which provide estimates at the state and county level) indicate that among individuals aged 50–64, no state in our sample experienced a reduction or increase in health insurance coverage of more than one percentage point between 2005 and 2006 or between 2005 and 2007 (United States Bureau of the Census 2005, 2006, 2007).

Analytic Strategy

For each of our hospitalization measures, we estimate the following regression model:

$$Pr(H_{ast}) = \Lambda\left(\begin{array}{l}\alpha + \beta age_a + \gamma year_t + \delta state_s + \\ \zeta age_a \times year_t + \theta age_a \times state_s + \kappa year_t \times state_s + \lambda age_a \times cov_{st}\end{array}\right) \quad (1)$$

where H_{ast} is an indicator variable coded as 1 for individuals from each age–state–time period cluster who were hospitalized for the condition under study and 0 otherwise, $\Lambda(\ )$ is the logit transformation, age_a is an indicator coded as 1 for individuals aged 65-plus and 0 for individuals aged 60–64, $year_t$ are year indicators for 2005–2007 (one omitted), $state_s$ is a set of 23 indicator variables (one omitted) for each of the states in our sample, and cov_{st} is the Medicare drug coverage rate for each state and year. Each cell is weighted by population size, as calculated from the Census. There are 276 observations (23 states $\times$ 2 age groups $\times$ 3 years $\times$ 2 outcomes—hospitalization versus no hospitalization). Weighting by population, the data represent 82,464,740 person-year observations. We are interested in the coefficient for the age-coverage interaction term, λ.

This specification is analogous to a difference-in-difference-in-differences (DDD) model.[2] It assesses whether hospitalization rates for Medicare beneficiaries changed more in states that had big Part D-induced changes in drug coverage relative to changes with smaller Part D-induced drug coverage changes. The indicator variables and associated interactions allow us to control for time-invariant differences in states and age groups within each

state, as well as general time trends that vary by state and age. For example, one concern in a state-level analysis of hospitalization rates is the substantial geographic variation in hospitalizations, which may be due to market-level provider characteristics rather than underlying differences in disease (Fisher et al. 2003). The state–age interactions will control for any age group-specific geographic differences in hospitalization rates across states, and our state–time period interactions will control for any age group-specific geographic differences in hospitalization trends. Ultimately we measure whether each state's time trend in hospitalizations for Medicare beneficiaries following the introduction of Part D, relative to the trend for near-elderly individuals, was systematically related to the impact of Part D on rates of drug coverage in the state.

A critical difference between the DDD model and the more common difference-in-differences (DD) model is that our approach allows us to compare the experiences of a group of patients whose coverage, adherence, and hospitalization histories would have been influenced by the introduction of Part D with another group who would not have been affected. A DD model would exclude this additional comparison, which could lead to incorrect inferences about the impact of the Part D policy change. For example, if a DD analysis focused only on 65-plus patients and demonstrated that higher coverage rates led to reductions in hospitalization rates, it could be the case that other characteristics of states with large coverage changes were driving the result. Adding the comparison with younger patients eliminates this concern, as we would expect these other characteristics to influence hospitalization rates for patients in both age groups.

To compute the estimated magnitude of the impact of Part D on hospitalizations using the results from our logistic regression models, we calculate two predicted hospitalization rates in 2007 for those aged 65-plus: a version using the 2007 average coverage rate, and a counterfactual version using the 2005 average coverage level. The second of these predicted rates is meant to reflect what the hospitalization rate would have been if there had been no change in coverage due to Part D. We hypothesize that the difference between these two predicted probabilities of hospitalization will be negative, reflecting the beneficial effects of drug coverage on adherence and adherence on avoiding hospitalization.

We estimate the standard errors for the model parameters clustering on observations from the same state (White 1980; Bertrand, Duflo, and Mullainathan 2004). Standard errors for other quantities of interest (e.g., the predicted hospitalization rates) are calculated using the delta method (Ai and Norton 2003). We perform all of our analyses using *Stata* statistical software, version 9.2 (StataCorp 2007).

RESULTS

Table 1 presents means for each of our analysis variables by age group and time period, weighted by population. The unadjusted hospitalization rate for any of our conditions among the elderly declined by 9.0 percent, from 501.3 per 10,000 in 2005 to 456.2 in 2007. For our nonelderly group, the rate of decline for the same measure was even larger, 11.8 percent, from 200.8 in 2005 to 177.1 in 2007. Moreover, the hospitalization rates vary significantly across conditions. For example, in 2005, 188.5 out of every 10,000 individuals aged 65-plus were hospitalized for CHF, while the rate for uncontrolled diabetes was 3.6 per 10,000.

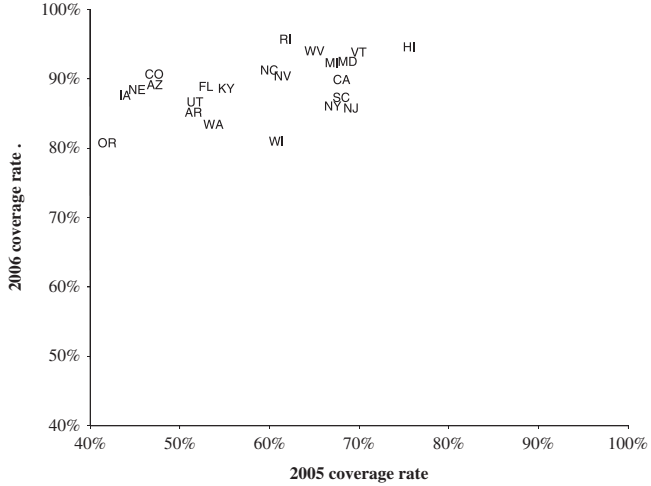
Table 1 also describes the increase in drug coverage among the elderly in our 23-state sample, from 61 percent in 2005 to 88 percent in 2007. While there was considerable variation in drug coverage before Part D, it shrunk dramatically after the introduction of the program in 2006 (Figure 1; the coverage rates for 2006 and 2007 are very similar). In 2006, no state had a Medicare prescription drug coverage rate lower than 81 percent. Medicare beneficiaries in every state experienced an increase in coverage, but the magnitude of the change varied significantly across states. For example, Iowa's coverage rate increased 43 percentage points (from 45 to 88 percent), while

Table 1: Condition-Specific Hospitalization Rates (per 10,000) and Coverage Rate by Year and Age Group

	2005		*2006*		*2007*	
	60–64	*65-Plus*	*60–64*	*65-Plus*	*60–64*	*65-Plus*
Any condition	200.8	501.3	190.2	478.6	177.1	456.2
Diabetes short term	3.9	3.6	3.8	3.3	3.7	3.2
COPD	38.9	76.4	35.3	70.1	33.2	68.3
CHF	54.4	188.5	51.2	183.4	46.4	171.6
Angina	7.1	9.4	6.2	8.4	5.4	7.4
Uncontrolled diabetes	2.9	3.6	2.9	3.6	2.8	3.7
Asthma	17.5	23.6	15.8	22.0	14.9	20.9
Stroke	37.5	112.6	37.4	110.0	36.1	106.8
AMI	38.7	83.6	37.5	77.8	34.7	74.4
Coverage	–	0.61	–	0.88	–	0.88
N	46	46	46	46	46	46
Weighted *N*	6,965,242	19,851,319	7,179,769	20,160,375	7,773,124	20,534,911

AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disorder.

Figure 1: Prescription Drug Coverage Rates among Medicare Beneficiaries 2005 and 2006



The figure depicts the 2005 prescription drug coverage rate along the *x*-axis, and the 2006 coverage rate along the *y*-axis, for elderly individuals in each of the 23 states in our analysis sample.

South Carolina's coverage rate changed by only 19 percentage points (from 68 to 87 percent). South Carolina had a much higher ESR coverage rate at baseline (35 versus 18 percent in Iowa), a higher dual eligible rate (19 versus 13 percent), and a higher rate of coverage through SPAP (8 percent; Iowa had no SPAP in 2005). Much of the 24 percentage point difference in the coverage change between these two states can be explained by Part D coverage: 48 percent of beneficiaries in Iowa enrolled in a Part D plan, compared with 29 percent in South Carolina. Because SPAP enrollees in South Carolina were moved to Part D, on net only 21 percent of the state's Medicare beneficiaries gained prescription drug coverage from the new Medicare benefit.

The regression results in Table 2 indicate that in aggregate, the Part D coverage change reduced hospitalizations for these conditions by 20.5 per 10,000. This is 4.1 percent of baseline admissions and about half of the total decline in admissions (Figure 2). This reduction is significant at the 0.01 level, as is the coefficient estimate on the age–coverage interaction. If we drop our control group of individuals aged 60–64 and run DD models (regressing

Table 2: Results

	Any Condition	*Diabetes Short Term*	*COPD*	*CHF*	*Angina*	*Uncontrolled Diabetes*	*Asthma*	*Stroke*	*AMI*
Regression coefficients									
Age 65-plus	0.9428***	0.1728	0.6924***	1.3509***	0.2231	0.3736**	0.5324***	1.0202***	0.6503
	−(0.0339)	−(0.1506)	−(0.0787)	−(0.0453)	−(0.1377)	−(0.1619)	−(0.0815)	−(0.0523)	−(0.0656)
Year = 2006	−0.0728***	−0.0122	−0.1461***	−0.0645***	−0.0187	0.0687*	−0.1557***	−0.0500***	−0.0214
	−(0.0081)	−(0.0372)	−(0.0191)	−(0.0132)	−(0.0376)	−(0.0387)	−(0.0236)	−(0.0139)	−(0.0145)
Age 65-plus 2006*	0.0524***	0.0581	0.0631*	0.0985***	0.0537	0.1419**	0.1527***	−0.0293	−0.0326
	−(0.0165)	−(0.0662)	−(0.0372)	−(0.027)	−(0.0686)	−(0.0714)	−(0.0341)	−(0.0262)	−(0.0405)
Year = 2007	−0.1479***	−0.0050	−0.2298***	−0.1603***	−0.2628***	0.2366***	−0.1888***	−0.1048***	−0.0985
	−(0.012)	−(0.0332)	−(0.0244)	−(0.0137)	−(0.0413)	−(0.0435)	−(0.0224)	−(0.016)	−(0.0128)
Age 65-plus 2007*	0.0737***	0.0496	0.0985***	0.1275***	0.0603	0.2088***	0.1634***	−0.0230	0.0014
	−(0.0124)	−(0.072)	−(0.0346)	−(0.0224)	−(0.0482)	−(0.067)	−(0.0369)	−(0.0229)	−(0.0391)
Age 65-plus coverage*	−0.1686***	−0.4292*	−0.1899	−0.2434***	−0.1358	−0.6081**	−0.4671***	0.0257	−0.0245
	−(0.0573)	−(0.2587)	−(0.1359)	−(0.0806)	−(0.2322)	−(0.27)	−(0.1386)	−(0.0903)	−(0.1216)
Constant	−4.0678***	−8.0689***	−5.6614***	−5.6029***	−7.8096***	−8.6911***	−6.5402***	−5.5925***	−5.6124
	−(0.0064)	−(0.023)	−(0.0134)	−(0.008)	−(0.0232)	−(0.028)	−(0.014)	−(0.0096)	−(0.0089)
N	276	276	276	276	276	276	276	276	276
Weighted *N*	82,464,740	82,464,740	82,464,740	82,464,740	82,464,740	82,464,740	82,464,740	82,464,740	82,464,740
Predicted probabilities									
Hospitalization rate per 10,000, 2007 coverage rates	449.6	3.1	65.6	167.7	7.1	3.2	20.1	106.0	73.8
Hospitalization rate per 10,000, 2005 coverage rates	470.1	3.5	69.2	179.2	7.3	3.8	22.8	105.3	74.3
Impact of coverage change	−20.5***	−0.4	−3.5	−11.5***	−0.3	−0.6**	−2.8***	0.7	−0.5
	(7.1)	(0.3)	(2.6)	(3.9)	(0.5)	(0.3)	(0.9)	(2.6)	(2.5)
Relative impact of coverage change	−4.4%***	−11.2%	−5.1%	−6.4%***	−3.7%	−15.5%**	−12.1%***	0.7%	−0.7%
	(1.5%)	(7.2%)	(3.7%)	(2.2%)	(6.4%)	(7.5%)	(3.8%)	(2.5%)	(3.3%)

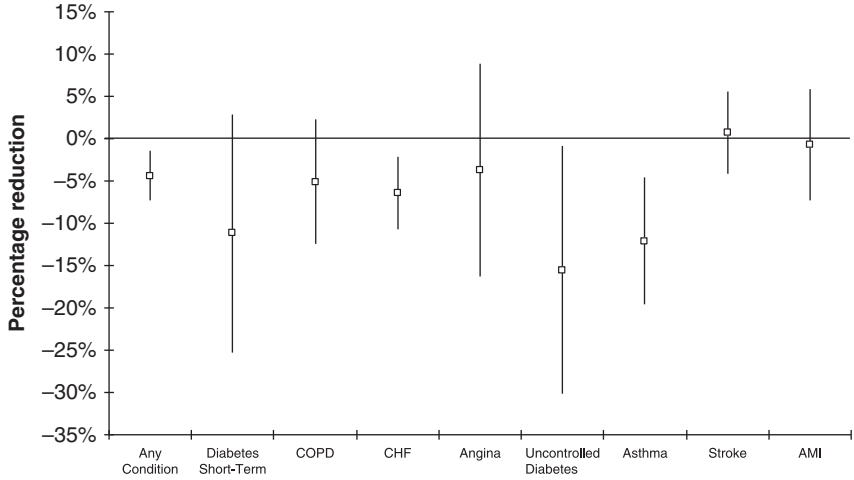
Notes. Coefficients for the state indicator variables, state–year interactions, and state interactions with age have been omitted. Standard errors in parentheses. Standard errors allow for clustering at the state level.

The first predicted probability describes the probability of hospitalization for each measure for an individual age 65-plus in 2007 using 2007 coverage rates and the second describes the probability of hospitalization for the same individual using 2005 coverage rates. For both predictions, all other variables have their values set to their mean. The relative impact of the coverage change is the absolute difference between the two predicted probabilities, divided by the probability of hospitalization using the 2005 coverage rates.

*p-value < .10; **p-value < .05; ***p-value < .01.

AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disorder.

Figure 2: Percentage Reduction in Hospitalization Rates Due to Coverage Change for Individuals Aged 65 and Older, 2007



The figure depicts the percentage reduction in the hospitalization rate, for individuals aged 65 and older in 2007. The percentage reduction is calculated as the difference in the predicted probability of hospitalization in 2007 assuming 2005 and 2007 coverage rates, respectively, divided by the predicted probability assuming 2005 coverage rates. The box for each condition represents the predicted percentage reduction, and the error bars represent the 95 percent confidence interval for each prediction.

hospitalization on age group, year and state indicators, and coverage), our estimate of the aggregate decline in hospitalizations is larger.

The results for specific conditions vary (Table 2). For example, the coefficient estimates for CHF and asthma are both significant at the 0.01 level, while the estimates for short-term complications of diabetes and uncontrolled diabetes are significant at the 0.10 and 0.05 levels, respectively. The estimates also indicate that Part D reduced hospitalizations for three of the other four conditions (stroke being the exception), but the effect is not statistically significant in any of these analyses. Because of multiple comparisons, we would expect some variation in the condition specific results do to pure randomness. Thus, we emphasize the findings from our aggregate measure. It is also worth noting that the percentage reduction in our aggregate measure lies within the 95 percent confidence interval for each of the eight specific conditions, as depicted in Figure 2.

Compared with estimates of what hospitalization rates would have been in the absence of increased coverage, Part D has had a significant impact on hospitalization for the conditions studied; among the 20 M elderly Medicare beneficiaries each year represented in our sample, the results suggest that Part D led to approximately 42,000 fewer hospitalizations each year after its introduction. If we were to apply this result to the entire 65 and older Medicare population, it would represent about 77,000 annual hospitalizations.

Results for other covariates were consistent with expectations. Older individuals have significantly higher hospitalization rates. Many of the state–time period interactions and age–state interactions are significant in each regression, which indicates that including state-specific time and age trends was an appropriate modeling choice (results not shown). Focusing on the aggregate hospitalization measure, the general trend (holding coverage constant) for all patients was a reduction in the hospitalization rate over time, although the rate of decline was lower for older individuals. (Full results from each regression are available from the authors upon request.)

We perform some additional analyses to assess the sensitivity of the results to our modeling assumptions. First, we assign the 2006 coverage estimates to the pooled 2006 and 2007 hospitalization data. Second, we pair the 2007 coverage estimates with the pooled 2006 and 2007 hospitalization data. In both analyses, the magnitude and statistical significance of our main results are essentially the same. Third, we run the regression on the aggregate hospitalization measure 23 additional ways, each time dropping a single state from the analysis (along with the state's indicator variable and its interactions with age and year). In all but one of these regression runs, the sign, magnitude, and statistical significance from these runs are very similar to the main results. Only the estimate for the regression that omits Florida leads to a sizable change: the coefficient estimate on the age–coverage interaction is lower, at -0.108 (compared with -0.169 in our main analysis), and the p-value of the estimate is .032 (compared with a p-value of .003). This reduces our estimates of the absolute and percentage reduction in admissions due to Part D to about 12.3 per 10,000 and 2.7 percent, respectively. Yet even this most conservative estimate is statistically significant and is consistent with our primary conclusion that Part D reduced the aggregate hospitalization rates for the conditions under study.

To assess the reasonableness of our findings, we compare our results to those one would expect based on estimates from our data and the literature of the parameters that determine the impact of Part D on coverage. Specifically, the impact of Part D on hospitalizations will depend on the extent to which Part D increased coverage, the extent to which coverage increases use of

prescription drugs, and the extent to which use of prescription drugs reduces hospitalizations. (The precise relationship between these parameters and the impact of part D on coverage is derived in an appendix.) We assume that Part D increased coverage by 28 percentage points (based on our data) and that drug coverage increased adherence by 21 percentage points (based on a report by Zhang et al. 2009), and that the average probability of adherence (combining those with and without coverage) is 0.60.

The most difficult parameter to estimate from the literature is the percent reduction in the likelihood of hospitalization due to adherence. Estimates in the literature will be sensitive to the population studied and do not span all of our conditions. Sokol et al. (2005) estimate that adherence reduces the likelihood of hospitalization by as much as 58 percent. We consider this our high-end estimate. Evidence from randomized clinical trials examining the impact of medications on outcomes report reductions in adverse events as high as 45 percent, and as low as 19.5 percent, depending on the medications being tested and the patient population under observation (Beta-Blocker Heart Attack Study Group 1983; The SOLVD Investigators 1991, 1992; Sacks et al. 1996; Long Term Intervention with Pravastatin in Ischemic Disease [LIPID] Study Group 1998; The Heart Outcomes Prevention Evaluation Study Investigators 2000; Brophy, Joseph, and Rouleau 2001; Heart Protection Study Collaborative Group 2002; The EURopean Trial on Reduction of Cardiac Events with Perindopril in Stable Coronary Artery Disease Investigators 2003).

These parameters suggest a range of Part D effect on the percentage reduction of the hospitalization rate of between 1.2 and 4.6 percent. The range would be higher if we were to assume Part D increased the generosity of coverage for those that had some coverage before Part D (as observed in Zhang et al. 2009). Our baseline point estimate of 4.1 percent is within that range, albeit at the high end. Our point estimate when Florida is excluded is 2.7 percent and that is well within the range. Thus, we believe it is reasonable to conclude, as we do, that Part D has a significant effect on hospitalizations.

DISCUSSION

Our analysis demonstrates that increased drug utilization induced by the introduction of Medicare Part D had measurable clinical benefits. Specifically, the change in drug coverage due to the passage of Part D—from 61 percent in 2005 to 88 percent in 2006 and 2007 in our analysis sample—led to a reduction of about 42,000 admissions from any of the conditions we studied, a 4.1

percent decline from 2005. This estimate reflects the actual change in drug coverage in our sample due to the introduction of Part D; a larger coverage increase would have increased the estimate of prevented hospitalizations.

Because our analysis is limited to data from the first 2 years of the Part D program, which may not be long enough to identify changes in hospitalization rates, our estimates may understate the impact of Part D. 2006 was a transition year for the Part D program. A number of individuals who would eventually become adherent due to their Part D coverage were likely in transition during 2006. Many waited until the May 15, 2006 deadline to enroll in a plan; Part D enrollment jumped from roughly 16–22 million between February and June of 2006 (Centers for Medicare and Medicaid Services [CMS] 2009). Anecdotal evidence suggests that others may have experienced delays utilizing their policies as plans and pharmacies worked to implement and submit claims under the new program, and still others may have delayed utilizing their benefit before discussing the appropriate drug regimen with a physician (Pear 2006). Thus, many Part D enrollees would have gained coverage for only a part of 2006. If the impact of adherence on health, and hence hospitalizations, may not be immediate, a longer time window might allow identification of larger effects. For example, cholesterol-lowering drugs have been documented to reduce AMI and stroke rates, but over a period of multiple years (LaRosa et al. 2005). Even with these data limitations, we have demonstrated that the change in coverage associated with Part D led to reduced hospitalization rates for four conditions that are plausibly adherence sensitive and for our aggregate measure.

There are other limitations to our study. First, our measures of prescription drug coverage are based on surveys, administrative records, and other imperfect data sources. This introduces imprecision into these coverage estimates, which may bias our findings toward zero. Moreover, our area-level analysis does not use individual-level characteristics such as medical history and prescription drug utilization. This will not bias our results unless these traits were changing systematically at the area level for the elderly relative to the nonelderly.

Second, our coverage data pertain to the entire Medicare population, but our analysis is confined to beneficiaries 65 and older. We expect that the coverage rates for the over 65 population are quite similar to the aggregate rates because the over 65 population comprises more than 80 percent of the total Medicare population. Data support this assumption; for example, data from the 2006 Medical Expenditure Panel Survey indicate that Medicare Part D coverage was 47 percent among all Medicare beneficiaries, and 47 percent among those 65 and older. Also, as described above, our statistical analysis

controls for any state-specific or time-period-specific difference in coverage between these two groups.

Third, a natural question is whether our analysis could have used individual-level data. While the CMS provides individual-level enrollment and claims data for beneficiaries enrolled in Part D, it is not possible using these data to ascertain each beneficiary's drug coverage status at baseline (i.e., in 2005), for example, through a former employer or Medicaid (CMS 2010). More important, nonrandom selection into Part D plans would complicate causal inference in an individual-level analysis; beneficiaries who were unobservably less healthy may have been more likely to enroll in the new program. Our area-level study design is analogous to an intention to treat analysis and therefore avoids the issue of nonrandom selection that would arise with an individual-level approach.

Fourth, one might argue that our state-level hospitalization rates should have been calculated with a different denominator: the number of individuals in each state with each of the conditions we studied. Under this approach one would assess the hospitalization risk of these patients alone. However, measuring disease prevalence is difficult and coding may be sensitive to changes in treatment patterns. Our analysis assumes that Part D did not alter the underlying prevalence of disease.

Fifth, the Part D "donut hole," which requires that beneficiaries cover the full cost of drugs beyond an initial coverage limit (in 2010, U.S.$2,830 in total drug expenses) and up a catastrophic coverage threshold (U.S.$6,440 in expenses), may affect adherence. Because we do not have individual-level drug claims, we cannot track drug spending throughout the year to assess the impact of this coverage gap. However, one might expect that individuals who reach the donut hole would reduce their adherence due to higher out-of-pocket costs. Recent work has demonstrated that compared with those who had coverage in the donut hole, beneficiaries who fell into the gap reduced adherence levels (Fung et al. 2010). Nevertheless, our results should reflect the total effect of Part D: the initial cost sharing, the lack of cost sharing in the coverage gap, and the cost sharing beyond the catastrophic coverage limit. Changes in the 2010 health care reform law eliminating the donut hole should have the effect of further improving adherence and reducing hospitalization rates for the conditions we have studied here.

A related concern is that we lack data on the generosity of benefits of different plans. In essence, we are measuring a combined effect of coverage expansion and generosity changes. For example, if generosity changes were greater in states with big coverage changes, then our estimates include the effect of not only gaining coverage but also of generosity increases. While our

data do not permit us to assess the impact of Part D holding generosity constant, we do provide reasonable estimates of the total Part D effect.

Finally, our findings do not address the impact of expanded prescription coverage on total program costs. A more comprehensive evaluation of this expansion of Medicare benefits would attempt to balance the benefits of the program (including those we identified) with the overall cost, recognizing that some of the Part D cost will be offset by reduced hospitalization costs.

Despite these limitations, our analysis confirms the positive clinical benefits derived from Part D. We estimate roughly 42,000 hospitalizations were avoided in our sample states from conditions amenable to drug coverage. The estimate for the entire Medicare population would be about 77,000. This is within the range of what one might predict based on estimates of the impact of Part D on drug use and the impact of drug use on hospitalizations.

Most directly, this finding bolsters the case for Part D and improved access to prescription drugs. While we did not conduct a full cost-benefit analysis, the findings illustrate that the benefits of expanded drug coverage extended beyond better financial protection. This is consistent with other findings based on analyses of individual insurers, suggesting that those results likely generalize.

More broadly, these results highlight the importance of recognizing the connections between different types of care. The design of Medicare tends to lead analysts to think about the program in silos, such as Part A (largely inpatient care), Part B (largely physician and outpatient services), and Part D (drugs). Yet this division is artificial. Beneficiaries require care to be coordinated across programs. Current efforts to bundle payments and improve care coordination are a step toward recognizing these connections and may provide incentives for providers to manage across the spectrum of care needs. Cross-program effects, such as those we investigate here, lend support for such efforts.

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NOTES

1. We use the term *adherence* to describe not only the maintenance of a prescribed course of drug therapy but also the initiation of drug therapy and compliance with the fully prescribed dose.
2. While DD and DDD models typically exploit a dichotomous "treatment" (e.g., the introduction of a new policy by a specific state at a point in time), our model uses a continuous treatment, the level of drug coverage for the elderly in each state and year.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Appendix SA2: ICD-9-CM Codes for Ambulatory Care Sensitive Conditions.

Appendix SA3: Derivation of Drug Coverage Estimates.

Appendix SA4: Decomposition of the Impact of Coverage on Hospitalization.

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