Medicare Beneficiaries and the Impact of Gaining Prescription Drug Coverage on Inpatient and Physician Spending

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Objective. To assess whether gaining prescription drug coverage produces cost offsets in Medicare spending on inpatient and physician services.

Data Source. Two-year panels constructed from 1995 to 2000 Medicare Current Beneficiary Survey, a dataset of Medicare claims and health care surveys from the Medicare population.

Study Design. We estimated a series of fixed-effects panel models to calculate adjusted changes in Medicare spending as drug coverage was acquired (Gainers) relative to the spending of beneficiaries who never had drug coverage (Nevers). Explanatory variables in the model include age, calendar year, income, and health status.

Principal Findings. Assessments of inpatient and physician services spending provided no evidence of overt selection behavior prior to the acquisition of drug coverage (i.e., there were no preswitch spikes in Medicare spending for Gainers). After enrollment, the medical spending of Gainers resembled those of beneficiaries who never had drug coverage. Overall, the multivariate models showed no systematic postenrollment changes in either inpatient or physician spending that could be attributed to the acquisition of drug coverage.

Conclusions. We found no consistent evidence that drug coverage either increases or reduces spending for hospital and physician services. This does not necessarily mean that drug therapy does not substitute for or complement other medical treatments, but rather that neither effect predominates across the Medicare population as a whole.

Key Words. Medicare, prescription drug coverage, physician expenditures, inpatient expenditures

Far-reaching changes in the Medicare program are expected with the passage of the Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (PL 108-172), not the least of which is planning for the expenditures of the approximately 8 million beneficiaries who lacked any drug benefits

beforehand. This group is particularly intriguing as they are likely to see the most significant improvement in their access to medications: if lack of drug coverage posed a barrier to getting necessary medications then beneficiaries without any drug coverage should exhibit considerable increases in prescription drug use once enrolled in the Medicare benefit. For policy makers trying to anticipate the impact of giving drug benefits to people without prior coverage, there are many questions about health and quality of life, but two relate to costs: (1) how much will the new benefit directly impact drug spending and (2) how much will it indirectly affect other medical spending, such as hospitalization and physician visits? The first question is straightforward and has been the subject of some study, although estimates vary depending on the study population and the analytic method. The second question stems from a less studied but widely held view that providing drug coverage may create cost-offsets through savings in other health care expenditures. The clinical literature cites many examples where pharmacological interventions reduce emergency and acute care treatments, although it is unclear how these findings translate to an entire population with diverse medical conditions. Both issues are important for informing expectations about the Medicare drug program as projections predict that the majority of Medicare beneficiaries without drug coverage will participate (Shea, Stuart, and Briesacher 2003–2004). This study addresses the questions framed above through comparisons of before and after spending patterns of Medicare beneficiaries who pick up drug coverage (Gainers), relative to those who never had it (Nevers). The analysis used 6 years of data from the Medicare Current Beneficiary Survey and modeling techniques suitable for studying insurance transitions. We treated gaining coverage as plausibly exogenous for the following reasons. Our study covered a period of large expansions in Medicare drug coverage, from 65 percent in 1995 to 77 percent in 1999 (Briesacher, Stuart, and Shea 2002). Previous studies have found most changes in private health plans are because of external circumstances of different plan offerings or new enrollment opportunities rather than pure consumer choice (Cunningham and Kohn 2000; Stuart, Shea, and Briesacher 2001; Rice et al. 2002). In addition, we tested the

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exogeneity assumption in this study by reestimating the models with only individuals least likely to select into drug coverage—those who gained employer-sponsored coverage.

We expected from prior research to find increases in medication use after gaining prescription coverage because of decreases in patients' out-of-pocket prices (Leibowitz, Manning, and Newhouse 1985; Gianfrancesco, Baines, and Richards 1994; Gluck 1999; Lillard, Rogowski, and Kington 1999; Pauly 2004). However, the literature was less clear about how medications influence spending for physician services and hospitalization. Economic theory specifies that the relationships depend on whether the medical services are complements or substitutes. The empirical research is quite meager on this topic, although it seems reasonable to believe physician services are a complement to medications since patients must visit physicians to get prescriptions. In contrast, hospitalizations may act as substitutes if outpatient medications prevent acute events, although this association is also largely untested in diverse patient cohorts like the Medicare population. Thus, we had a cautious expectation of an inverse relationship between inpatient costs and prescription drugs.

Our analytical approach addresses two important weaknesses in the literature on health insurance coverage and medical care utilization. The first is our use of longitudinal data. Most analyses use cross-sectional data, which cannot be used to assess changes in medical care need or deteriorations in health (Kasper, Giovanni, and Hoffman 2000). This makes it difficult, if not impossible, to isolate the impact of insurance on health care spending from other influences because of differences within and across individuals. If, instead, individuals are followed over time, the temporal path of medical expenditures can be identified prior to the decision to acquire insurance coverage. Our longitudinal analysis assessed this observable element of selection as well as used a fixed-effects framework to control for time invariant factors.

The second contribution of this study is a narrow focus on gaining drug coverage. Analyses of losing insurance may be less useful for understanding the impact of acquiring coverage if these behaviors are not inversely related (Burstin et al. 1998; Long, Marquis, and Rodgers 1998). For example, individuals who lose their coverage may attempt to maintain the levels of care established while insured, in contrast to people who gain coverage and must learn to use the health care system as insured people (Stuart and Coulson 1993). In a study of adults who gained Medicaid or private health insurance, Kasper, Giovanni, and Hoffman (2000) detected relatively high levels of

access problems for Gainers even after becoming insured. Alternatively, research that combines the gaining and losing samples together as the “intermittently uninsured” may be masking the unique issues facing people when acquiring insurance (McWilliams et al. 2003).

The literature specific to drug coverage is growing but much of it suffers from the methodological issues described above (Stuart and Coulson 1993; Lillard, Rogowski, and Kington 1999; Atherly 2002). Studies with pre- and postenrollment data on expansions in Medicaid or state drug assistance programs offer mixed findings. A large decline in hospital spending followed an expansion in the drug formulary of the South Carolina Medicaid program for an under age 65 population (Kozma, Reeder, and Lingle 1990). Similarly, Lingle, Kirk, and Kelly (1987) detected lower inpatient expenditures after the implementation of New Jersey’s pharmaceutical assistance program for adults aged 65 or older. In contrast, Gilman et al. (2003) examined changes in Medicare spending after Vermont implemented two prescription drug programs for the state’s low income Medicare beneficiaries. Their study found no cost offsets to the Medicare program—in fact, inpatient spending increased between 25 and 45 percent in the first year and physician services increased 9–17 percent, although subsequent expenditures returned to preenrollment levels.

METHODS

Data Source

The dataset for this study is a set of 2-year panels constructed from the 1995 to 2000 Medicare Current Beneficiary Survey (MCBS). The MCBS is a longitudinal panel survey of a representative national sample of the Medicare population conducted under the auspices of CMS. Begun in the fall of 1991, over 12,000 Medicare beneficiaries are sampled from Medicare enrollment files and surveyed three times a year with computer-assisted personal interviews. The MCBS links Medicare claims to survey-reported events to provide complete expenditure and source of payment data on all health care services, including prescription drugs. The interview also collects information on public and private forms of health insurance such as the beginning and end dates of coverage and whether coverage includes prescription drugs.

Sample Selection Criteria

Our sampling frame included all fee-for-service beneficiaries with Parts A and B coverage during years 1995–2000. This criterion excluded beneficiaries

enrolled in Medicare HMOs because they have no itemized Medicare claims. We examined the health insurance information of each sampled individual over a period of 2 years and excluded persons for the following reasons: no enrollment dates or multiple gains into and out of drug coverage ($n = 1,601$); lost drug coverage ($n = 1,439$); or held it continuously ($n = 12,210$). Our final sample consisted of two mutually exclusive groups: people who gained drug coverage (Gainers, $n = 1,488$) during the observation period and people who had no evidence of drug coverage (Nevers, $n = 4,366$).

We also identified a subsample of people who gained drug coverage near the end of the year ($n = 60$). This group was necessary to address an MCBS data limitation of providing drug-spending levels at only the annual level while the duration of drug coverage spanned one to eight quarters. The calendar-end subsample had at least three quarters of drug spending without drug coverage in a calendar year followed by at least three quarters of drug spending with drug coverage in the following calendar year. Our subsample provides pilot evidence on the magnitude of changes in drug spending after gaining drug coverage. This information is necessary for establishing the mechanism by which drug coverage might influence medical care spending through increased use of medications.

Study Variables

We examined three dependent variables in the models: total prescription drug expenditures (out-of-pocket costs isolated for subanalysis), Medicare inpatient hospital expenditures, and Medicare physician expenditures. Prescription drug spending comes from the MCBS interview, includes only prescribed medications and is available as annual estimates. We assessed Medicare spending for inpatient hospital and physician expenditures directly from the Medicare claims records with the dates of service. Medicare inpatient spending covers hospitalization and emergency room visits. Medicare physician spending includes doctor visits, outpatient hospitalization, physical therapy, laboratory tests, durable medical equipment, and some outpatient mental health services. Claims estimates were summed for each month and then averaged over a quarter to smooth out the estimates.¹ For the multivariate models, we also trimmed the quarterly expenditure data at 2 standard deviations above the mean ($> \$3,684$ for inpatient and $> \$548$ for physician) to address extreme outlier values.²

The principal independent variable was a set of 14 indicators representing the time order of medical spending relative to the quarter of drug

coverage enrollment. First, we identified all beneficiaries acquiring drug coverage and isolated the quarter in which the change occurred. We then tracked quarterly Medicare spending as relative to the switch quarter, allowing us to observe up to seven quarters of prior spending (e.g., a person gaining in the last quarter of study observation) and seven quarters postspending (e.g., a person gaining in the first quarter of study observation). For example, an indicator of “+4” means the fourth quarter after gaining drug coverage, while “−4” means the fourth quarter before the gain. For the Nevers group, we assigned a random switching quarter to serve as their pre- and postpoint of reference. The other independent variables are: age (coded as a continuous variable and age squared), a set of dummy variables indicating the calendar year, and a health status index derived from the Diagnostic Cost Group Hierarchical Condition Category (DCG/HCC) risk adjuster. The DCG/HCC risk adjuster identifies the presence of up to 189 medical conditions in the diagnoses fields in Medicare claims records. The adjuster applies previously calibrated weights to create a single risk score (denoted as *ybase*) of the patient’s expected Medicare expenditure. In our models, we normalize *ybase* by dividing each predicted value by the mean *ybase* in the main population-based sample. Thus, a person with mean predicted expenditure equal to the population average is scored 1.0. The use of predicted as opposed to actual health care expenditures isolates individuals’ need for medical care (presumably exogenous) from their actual use of medical care (presumably jointly determined with their insurance choices).

Multivariate Model

We chose a fixed-effects panel estimator and difference-in-difference (DD) model to explore the dynamic aspects of individual behavior around gaining drug coverage. The fixed-effects estimator is well suited for our data structure, and its strengths include direct assessments of spending changes and explicit handling of individual-level heterogeneity.³ The unit of observation was the person-quarter. The specification of the model occurred in two steps. In the first step, we assessed the extent that observable selection exists between drug insurance and nondrug spending. The basic model can be summarized as:⁴

$$Y_{it} = \alpha_i + Z_{it}\beta_1 + Z_{it}R_i\beta_2 + X_{it}\beta_3 + H_{it}\beta_4 + C_t\beta_5 + \varepsilon_{it}, \quad (1)$$

where Y_{it} is quarterly Medicare expenditures for beneficiary i in quarter t ; α_i is the intercept for each individual; Z_{it} indicates the time order of each quarter relative to enrollment date, $Z_{it}R_i$ is an interaction term indicating quarterly observations from Gainers,⁵ X_{it} represents a vector of time-varying

beneficiary-level demographic characteristics; H_{it} is the annual HCC risk index measured as a ratio of predicted individual spending over predicted average spending; and C_t is a set of year dummy indicators.

The main coefficients of interest are the β_2 's, which express the difference in Medicare spending between Gainers and Nevers in each quarter relative to the reference quarter. These coefficients capture differences in spending conditioned on the model covariates, Z , X , H , C , and the fixed effects. We plotted these coefficients in graphs to provide a visual expression of the likelihood that the postgain effects are influenced by unmeasured factors in the preperiod (i.e., adverse selection). If significant differences are present in the pregain coefficients, then an additional step is needed to control for them. This approach is not a definitive test of selection but rather a guide on the magnitude of influence.

The second step is a traditional DD model that compares both the pre- and postspending of Gainers to the period-matched spending of the Nevers. This model is reasonable if any changes in spending over time would have been the same for both groups except for any induced spending attributable to drug coverage. Controlling for observable factors, our DD model holds that the difference between Gainers and Nevers in the postperiod constitutes the insurance effect and period-related factors, while the difference in the preperiod reflects only the period-related factors. Thus, any remainder between the two differences equals the insurance effect for Gainers. The model elements are same as for equation (1) except the Z variables have been replaced by a single indicator of postenrollment observations, and the main effect of being a Gainer has been added as R and specified below:

$$Y_{it} = \alpha_i + Z_{it}\beta_1 + R_i\beta_2 + Z_{it}R_i\beta_3 + X_{it}\beta_4 + H_{it}\beta_5 + C_t\beta_6 + \varepsilon_{it}. \quad (2)$$

The coefficient of β_3 is the test that changes in spending for Gainers are different from preenrollment levels and from those of Nevers. We used *SAS* and *STATA* statistical software to conduct all analyses. None of the estimates used the MCBS sampling probability weights.

RESULTS

Table 1 presents the sample sizes and descriptive characteristics of the Gainer and Never samples from the 1995 through 2000 MCBS. The average duration of drug coverage for Gainers is 4.8 quarters and the types of sources are: 46.2 percent self-purchased, 37.3 percent employer-sponsored, 10.4 percent

Table 1: Sample Size and Characteristics of Medicare Beneficiaries in 2-year Study Panels, $n = 5,854$

<i>Sample Size (Unweighted)</i>	<i>Status of Drug Coverage during 2 Years</i>	
	<i>Gainners</i>	<i>Never</i>
Total (n)	1,488	4,366
Panel y9596	282	960
Panel y9697	269	951
Panel y9798	308	900
Panel y9899	311	839
Panel y9900	318	716
Type of gained drug coverage (%)		
Self-purchased	46.2%	NA
Employer-sponsored	37.3	
Medicaid	10.4	
Other public programs	13.3	
Undetermined	3.4	
Average duration of coverage (quarters)	4.8	0
<i>Baseline characteristics</i>		
Gender	<i>n (%)</i>	<i>n (%)</i>
Male	617 (41.5)	1,709 (39.1)
Female	871 (58.5)	2,657 (60.9)
Age		
<65	145 (9.7*)	100 (2.3)
65–69	165 (11.1)	430 (9.8)
70–74	359 (24.1)	1,004 (23.0)
75–79	290 (19.5)	921 (21.1)
80+	529 (35.6*)	1,911 (43.8)
Metropolitan status		
Nonmetro area	532 (35.8*)	1,819 (41.7)
Metro area	956 (64.2*)	2,547 (58.3)
Detailed census region		
New England	59 (4.0)	117 (2.7)
Middle Atlantic	247 (16.6*)	537 (12.3)
East North Central	259 (17.4)	897 (20.5)
West North Central	119 (8.0*)	587 (13.4)
East South Central	102 (6.9)	341 (7.8)
West South Central	159 (10.7)	471 (10.8)
Mountain	82 (5.5)	229 (5.2)
Pacific	135 (9.1)	285 (6.5)
South Atlantic	326 (21.9)	902 (20.7)
YBase index		
Panel average	0.94*	0.91

* $p < .05$.

Source: 1995–2000 MCBS.

MCBS, Medicare Current Beneficiary Survey; NA, not applicable.

Medicaid, 13.3 percent other public programs, and 3.4 percent undetermined (note percentages are greater than 100 percent because of people enrolling into multiple plans). In general, the groups are similar with a few exceptions: Gainers are more likely to be disabled beneficiaries under age 65 than the Nevers (9.7 versus 2.3 percent, $p < .05$) and also less likely to be the oldest old (35.6 versus 43.8, $p < .05$). The Gainer sample more often lived in metropolitan areas compared with the Never sample (64.2 versus 58.3 percent, $p < .05$) and in the Middle Atlantic area of the country (16.6 versus 12.3 percent, $p < .05$). The Gainer group also generated a higher average HCC risk ratio than the Never group (0.94 versus 0.91, $p < .05$).

Tables 2 and 3 show the annual expenditures for prescription drugs, inpatient hospitalizations and physician services arrayed according to drug coverage status. Table 2 summarizes the medical spending levels for the entire sample as well as shows the proportion with any utilization. Here, the spending levels for prescription drugs matched a priori expectations for the two groups but expenditures for the other services varied in conformance: Gainers had higher drug expenditures than Nevers, but the average physician and inpatient spending is notably similar. On average, Gainers spent about 20 percent more on medications than Nevers (\$711 versus \$565, $p < .05$), but were equally likely to purchase any prescription drugs (86.9 versus 88.2 percent, NS). In comparison, average inpatient spending is about the same

Table 2: Univariate Statistics on Annual Prescription Drug, Inpatient, and Physician Expenditures of Medicare Beneficiaries by Drug Coverage Status, $n = 5,854$

<i>Medical Expenditures</i>	<i>Status of Drug Coverage during 2 Years</i>	
	<i>Gainers</i>	<i>Nevers</i>
Prescription drug		
Mean (SE)	\$711 (26)	\$565 (10)
Percent with expenditures	86.9	88.2
Mean among those with any expenditures (SE)	\$818 (29)	\$641 (10)
Inpatient		
Mean (SE)	\$1,560 (158)	\$1,527 (84)
Percent with expenditures	16.9	16.0
Mean among those with any expenditures (SE)	\$9,247 (773)	\$9,549 (404)
Physician		
Mean (SE)	\$1,006 (38)	\$1,024 (24)
Percent with expenditures	89.9	92.0
Mean among those with any expenditures (SE)	\$1,119 (41)	\$1,114 (25)

Source: 1995–2000 Medicare Current Beneficiary Survey.

Table 3: Sample Size and Annual Prescription Drug Spending before and after Drug Coverage Switch for Medicare Beneficiaries with Calendar-End Changes in Drug Coverage

<i>Sample Size (unweighted)</i>	<i>Year before Switch</i>	<i>Year after Switch</i>	<i>Difference</i>
<i>N</i>			
Gainers	60	60	–
Nevers	177	177	–
Average total Rx spending (SE)			
Gainers	\$664 (125)	\$1,101* (194)	+65.8%
Nevers	\$547 (47)	\$592 (51)	+8.3%
Average out-of-pocket Rx spending (SE)			
Gainers	\$650** (125)	\$506 (77)	– 22.1%
Nevers	\$547 (47)	\$592 (51)	+8.3%

* $p < .05$, test is Gainers versus Nevers in year after switch.

**OOP not equal to total because of rounding of partial quarters to full quarters.

Source: 1995–2000 Medicare Current Beneficiary Survey.

(\$1,560 Gainers versus \$1,527 Nevers, NS) as is physician spending (\$1,006 Gainers versus \$1,024 Nevers, NS).

Table 3 provides preliminary information on changes in prescription drug use before and after a gain in coverage. The sample is limited to Gainers with year-end changes and Nevers with matched switching dates. Estimates for total drug spending are statistically the same for the Nevers and Gainers in the year before the switch (\$664 Gainers versus \$547 Nevers, NS), however, spending levels diverge significantly in the year after the switch (\$1,101 Gainers versus \$592 Nevers, $p < .05$). On average, Gainers spent almost 66 percent more on prescription drugs in the year following the acquisition of drug coverage, compared with the Never sample, which spent 8.3 percent more. Out-of-pocket spending dropped over 20 percent for Gainers compared with increasing 8.3 percent for Nevers, however this difference was not statistically significant.

The next set of figures (Figures 1 and 2) displays patterns in quarterly Medicare inpatient and physician spending by the Gainer group before and after the change in drug coverage, relative to the no coverage group. The estimates have been adjusted for calendar year, demographics, and health status (regression output for these graphs are available from the authors). For inpatient spending, we see similar increases during the entire period for both groups. Right before the acquisition of drug coverage by Gainers, we observe a slight gain in inpatient spending, although nothing of statistical significance (Figure 1). Following the switch, there appears to be no apparent sensitivity to

Figure 1: Adjusted* Average Changes in Inpatient Spending before and after Drug Coverage Switch for Gainers versus Nevers

*Adjusted for year, age, marital status, income urban residence, and health status.
Dashed lines are 95% confidence intervals.

the new coverage until after the 5th quarter—inpatient spending shows slight evidence of divergence as Gainers begin spending less than Nevers, although the difference is not statistically significant until the 7th quarter ($p < .10$). We see similar patterns for Medicare physician spending. In comparing the physician spending of the Gainer to the Never sample (Table 4), there is again no apparent change around the immediate period of gaining drug coverage. Here too, the Gainers show no statistically significant difference in Medicare spending from Nevers. Taken together, the adjusted patterns of inpatient spending and physician spending suggest no obvious relationship to drug coverage.

The last two tables (Table 4 and 5) summarize the findings of the difference-in-difference models. Each estimate in this table shows the residual spending of persons gaining drug coverage in the postperiod relative to spending in the preperiod and by persons without any drug coverage. Number of groups refers to the unique persons with spending. Each person has a minimum of eight quarters of observations, creating a total of 45,384 person quarters. Observations differ across inpatient and physician models because people without spending changes contribute no observations to the models.

Figure 2: Adjusted* Changes in Average Physician/Supplier Spending before and after Drug Coverage Switch for Gainers versus Nevers

*Adjusted for year, age, marital status, income urban residence, health status, and fixed effects.

Dashed lines are 95% confidence intervals.

The coefficients on “Post $\times$ Gain” indicate the test of Gainer spending after acquiring drug coverage relative to preacquisition spending and that of the Nevers. In the case of inpatient spending, the postcoverage differences are negative for Gainers versus Nevers and in the expected direction, although the estimates are not statistically significant. For physician spending, the annual postperiod differences are again negative for Gainers versus Nevers and not in the hypothesized direction, although the difference is not statistically significant. As a sensitivity test, we reestimated our models with only people gaining employer-sponsored coverage and found essentially the same results, although the standard errors were relatively large with the smaller sample.

DISCUSSION

We draw two conclusions from this study. First, our subsample analysis suggests that gaining prescription coverage may increase drug expenditures by as

Table 4: Difference-in-Differences Model of Total Inpatient Spending for Gainers and Nevers

<i>Fixed-Effects (within) Regression</i>					
<i>Group Variable (i): baseid</i>					
<div> R^2 : within =0.0036 between =0.0035 overall =0.0007 Corr(u_i, Xb) = - 0.8453 </div>					
<div> Number of obs =13, 680 Number of groups =1, 401 Obs per group : min =8 avg =9.8 max =16 F(14, 12265) =3.19 Prob > F =0.0000 </div>					
<i>Total Inpatient</i>	<i>Coefficient</i>	<i>SE.</i>	<i>t</i>	<i>p> t </i>	<i>[95% Confidence Interval]</i>
y1996	187.791	54.95742	3.42	0.001	80.06581 295.5162
y1997	197.1407	79.44047	2.48	0.013	41.42485 352.8565
y1998	278.7367	103.0436	2.71	0.007	76.75515 480.7183
y1999	384.1231	127.8534	3.00	0.003	133.5104 634.7359
y2000	441.7032	150.1892	2.94	0.003	147.3087 736.0976
Age	- 336.8673	434.3684	- 0.78	0.438	- 1,188.298 514.5632
Age2	1.850741	2.72236	0.68	0.497	- 3.485513 7.186995
Married	10.11199	241.6825	0.04	0.967	- 463.6238 483.8478
Income	.1033875	1.45629	0.07	0.943	- 2.751171 2.957946
Metro	- 145.9165	716.1161	- 0.20	0.839	- 1,549.617 1,257.784
HCC Index	121.5006	35.7935	3.39	0.001	51.33974 191.6615
Postperiod	44.89839	37.38742	1.20	0.230	- 28.38683 118.1836
Gain	- 22.63968	135.5702	- 0.17	0.867	- 288.3786 243.0992
Post × gain	- 14.70328	63.81229	- 0.23	0.818	- 139.7854 110.3789
_cons	14,946.69	17,388.75	0.86	0.390	- 19,138 49,031.38
sigma_u	931.39804				
sigma_e	1,420.2969				
rho	.30072056	(fraction of variance because of u_i)			

much as 66 percent in the first year following a year without prior coverage. The increase was expected, but the size of the estimated effect is among the largest found in prior research, where estimates ranged from 18 to 60 percent (Leibowitz, Manning, and Newhouse 1985; Gianfrancesco, Baines, and Richards 1994; Gluck 1999; Lillard, Rogowski, and Kington 1999; Pauly 2004). These results are based on a small, nonrandomly selected sample and offer only preliminary evidence of how much drug costs might rise for the large group of uninsured beneficiaries likely to take up the new Medicare drug plan. Additionally, it is clear that Medicare is offering a less generous plan than what beneficiaries have traditionally had through employers or the public sector. The difference in generosity would ameliorate the demand-inducing

Table 5: Difference-in-Differences Model of Physician Spending for Gainers and Nevers

Fixed-Effects (within) Regression
Group Variable (i): baseid

Number of obs =45,384
Number of groups =4,054
Obs per group : min =8
 avg =11.0
 max =16

R^2 : within =0.0066
 between =0.0242
 overall =0.0098

Corr(u_i, Xb) = - 0.3113

$F(14, 41316) = 19.68$
Prob > $F = 0.0000$

<i>Total Physician</i>	<i>Coefficient</i>	<i>SE</i>	<i>t</i>	<i>p> t </i>	<i>[95% Confidence Interval]</i>	
y1996	9.100585	3.430918	2.65	0.008	2.375913	15.82526
y1997	14.25092	4.949754	2.88	0.004	4.549295	23.95254
y1998	22.28622	6.533179	3.41	0.001	9.481051	35.09139
y1999	29.73888	8.153666	3.65	0.000	13.75752	45.72024
y2000	33.8768	9.628832	3.52	0.000	15.00408	52.74951
Age	-20.6048	20.90089	-0.99	0.324	-61.57099	20.36139
Age2	.122362	.1327581	0.92	0.357	-.1378466	.3825706
Married	-17.61857	12.10421	-1.46	0.146	-41.34308	6.105949
Income	-.0014219	.0547972	-0.03	0.979	-.1088255	.1059817
Metro	-22.75821	37.74338	-0.60	0.547	-96.73604	51.21962
HCC Index	29.52116	3.312933	8.91	0.000	23.02774	36.01458
Postperiod	19.03616	2.345403	8.12	0.000	14.43912	23.6332
Gain	.8919971	7.274963	0.12	0.902	-13.36709	15.15108
Post × Gain	-2.738953	4.122824	-0.66	0.506	-10.81978	5.341871
_cons	900.9817	827.3328	1.09	0.276	-720.6082	2,522.572
sigma_u	94.073779					
sigma_e	168.21478					
rho	.23824516	(fraction of variance because of u_i)				

effect of coverage and thus limit additional spending. Our sample of people who gained drug benefits found, on average, over half of their medication expenses (54 percent) covered after gaining insurance coverage.

Second, the higher spending on drugs among those gaining coverage appears to have had little aggregate impact on spending for Medicare-covered services. This was a somewhat surprising finding given the higher spending that our total sample of Gainers incurred for medications relative to Nevers. During a period of increasing medication spending, we found physician spending remained relatively stable for Gainers, while their inpatient spending showed modest signs of dropping after about a year and a half, although these predictions are not statistically significant. Overall, we found no

consistent evidence that gaining drug coverage reduces spending for hospital and physician services. These findings concur with those of the Congressional Budget Office and Gilman et al. in the Vermont drug plan evaluation (U.S. Congressional Budget Office 2002; Gilman et al. 2003).

The usual caveats apply to drawing causal inference from limited samples based on observational data. First, the distinction may be somewhat arbitrary between people who gain drug coverage and those who lose it or lack coverage for indeterminate periods. Insurance status is a highly fluid measure and people with unstable coverage are likely to experience multiple entries and exits (Short and Freedman 1998; Stuart, Shea, and Briesacher 2001). Our exclusion criteria mean that the study results cannot be generalized to the entire Medicare population, particularly those in managed care plans. It is possible that the longitudinal observation period was too short in duration to capture the clinical benefits of medications that influence use of hospitals and physicians. Many of the prescription drugs used by Medicare beneficiaries are taken over the course of many years to slow the effects of disabling disease and thus related changes on demand for medical services may share a similarly lagged effect. In an ad hoc analysis, we reestimated the DD model with post-period defined as 1 year after gain. The Part B model coefficient changed from -2 to $+2$, $p < .5$. The Part A model coefficient changed from -14 to -58 but statistical significance was $p < .3$ as the standard errors were large. It is also important to note that the results reflect the marginal impact of drug benefits and not the full impact of drug therapy. Our results show high levels of medication use even among the uninsured, thus the impact of drug coverage refers to only the prescription spending above what the uninsured are spending.

On the technical side is the question of whether the analytic approach produces unbiased and precise estimates of treatment effects. The longitudinal approach attempted to assess the presence of observable selection into drug coverage, which is individuals changing their coverage status in response to anticipated changes in their expenditures. We observed no pregain patterns in Medicare spending that would indicate selection. Clearly, this finding is not definitive evidence of an exogenous relationship but it raises questions about the influence of expected hospital and physician spending on drug coverage decisions. Future research should more directly test these relationships. In the meantime, the longitudinal model of Gainers versus Nevers most closely approximates the changes that can be expected for the uninsured segment of the Medicare population once a Medicare drug benefit is implemented.

We believe the method described in this study offers a valuable approach for evaluating the impact of PL 108-172 on Medicare beneficiaries

without prior drug coverage. Future research in this area should study a larger sample of Gainers for a longer period of time. Our analysis detected a tantalizing drop in inpatient spending about five quarters postgaining coverage, which needs further investigation with larger samples and longer observation periods. Future analyses should also take into account the generosity of coverage gained and the personal resources available to beneficiaries. Lastly, the impact of drug spending may be focused in particular disease areas, which should be explored in subsequent work.

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NOTES

1. We also assessed the model with monthly spending but found the estimates were volatile and the display prone to distracting "noise."
2. We also estimated the model with logged and square-root transformations and found the model fit improved a few percentage points in some cases but the main findings remained the same. In the end, we used the trimmed raw values for ease of interpretation and presentation.
3. Limitations of the fixed-effects panel model include no estimates for time-invariant effects such as gender or race, and restricted generalizability. Strictly speaking, the fixed parameters of the individual-level intercept terms mean that common-level coefficients are conditional upon the members of the sample. We accepted this limitation rather than present the results from random effects panel models as the correlation between the individual-level errors and regressors was quite high, exceeding 0.84 in some cases. We also assessed the fixed-effects models for autocorrelated disturbances as it seemed likely that the pattern of spending (and residuals) in one quarter may be a fair indicator of spending in the next period. Our evaluation found that the autocorrelation never exceeded 0.10 in estimators with first-order correction for autoregression and the resulting changes in the coefficients and standard errors were quite modest.
4. We considered a 2-part model but in the end used a 1-part model to provide estimates of spending changes across the entire study population rather than just for users of services.
5. The *Z* variable is specified as 14 dummy variables arrayed as seven quarters pre-gain and seven quarters postgain. The quarter of enrollment is always equal to zero. The *R* variable is a group indicator = 1 for Gainers and 0 for Nevers.

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