Medicare Part D and Prescription Drug Utilization

Gary V. Engelhardt
Syracuse University

Abstract

This paper uses the substantial increase in prescription drug insurance coverage from the adoption of Part D to generate new estimates the impact of coverage on drug utilization. The analysis uses detailed panel data on the elderly before and after the implementation of Part D drawn from the 2005 and 2007 Prescription Drug Study (PDS), administered as a supplement to the Health and Retirement Study (HRS), a large nationally representative survey of Americans aged 50 and older. Fixed-effect estimates suggest that gaining coverage results in a 15% increase in utilization. These results are consistent with the lower end of estimates in the literature. Gaining coverage also is associated with a 20- 50% reduction in the incidence of cost-related non-adherence. However, even among the uninsured, only a relatively small proportion of drugs (12%) are associated with episodes of cost-related non-adherence. So, these large reductions apply to a small slice of all drugs. Overall, it does not appear that all of the increased utilization can be accounted for by the loosening of financial constraints from gaining insurance coverage. The results of the analysis leave open the possibility of a substantive role for moral hazard.

The impact of prescription drug insurance coverage on drug utilization has been an important topic in the last fifteen years in health economics and health research, both leading up to and after the implementation of Medicare Part D. A key policy concern, and indeed motive for expansions of coverage, is that the uninsured under-consume drugs because of financial constraints, with the primary avenue being cost-related non-adherence in drug regimens. Furthermore, such non-adherence has direct adverse health consequences (Sokol et al., 2005; Heisler et al., 2008). If true, then a key tradeoff in the design of optimal prescription coverage is the balance between the health and financial benefits of reductions in cost-related non-adherence (Madden et al., 2008) and excessive utilization via moral hazard (Pauly, 2004).[1]

Unfortunately, empirical analysis of the impact of insurance coverage on utilization faces two important challenges. First, the presence of unobserved heterogeneity in the demand for prescription drugs may bias estimated impacts on utilization. For example, if those with a high demand for prescription medications also are more likely to have coverage, then standard estimates of the impact of coverage on utilization will be biased upward. Second, as emphasized by Pauly (2004), it is sometimes difficult to interpret (even unbiased) estimates. On the one hand, the finding of a small impact of coverage on utilization may suggest a small role for moral hazard. On the other hand, a small impact may suggest that the particular form of insurance is not very effective in ameliorating the effect of financial constraints. In practice, it can be difficult to separate these effects.

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[1] Of course, more broadly this tradeoff would include the social value of all health and consumption-smoothing benefits vs. the costs of adverse selection and welfare diminishing moral hazard. To the extent price exceeds marginal cost for some pharmaceuticals, some moral hazard may be welfare improving. These broader issues are not examined here.

This paper uses the substantial increase in prescription drug coverage for the elderly that resulted from the adoption of Part D to generate new estimates the impact of prescription drug insurance coverage on drug utilization. The analysis uses detailed data on a strongly balanced panel of those 65 and older (the "elderly" as defined for this study), observed before and after the implementation of Part D in 2006. The data are drawn from the 2005 and 2007 Prescription Drug Study (PDS), administered as a supplement to the Health and Retirement Study (HRS), a large nationally representative survey of Americans aged 50 and older. These rich survey data contain information on prescription drug insurance coverage, utilization, as well as drug-level information from a roster of prescribed medicines.

There are two main innovations. First, the PDS panel data allow for the use of fixed-effect estimators to obtain consistent estimates of the impact of coverage in the presence of time-invariant unobserved heterogeneity in the demand for prescription drugs. Second, the PDS asked separate sets of questions on drug utilization, vintages, and cost-related non-adherence that, in principle, allow for a disentangling of the impact of insurance on utilization from that on the relaxation of financial constraints.

Using the PDS data, the passage of Part D was associated with a substantial increase in prescription drug coverage from public sources and a decrease in prescription drug coverage from private sources. The fixed-effect estimates suggest crowd-out of 73% and that, overall, the expansion of Part D raised prescription drug insurance coverage for the elderly by 10 percentage points. These results are remarkably consistent with the findings of Engelhardt and Gruber (2011), who developed a different identification strategy based on instrumental variable estimation and data from the

Medical Expenditure Panel Survey (MEPS). This temporal increase in coverage then is used to identify the impact of coverage on utilization. In particular, the fixed-effect estimates indicate that gaining coverage results in a 15% increase in utilization, as measured by the number of prescription drugs taken. These results are consistent with the lower end of estimates in the literature.

Using a variety of measures, including the frequency of unfilled, skipped, or stopped prescription regimens due to cost-related issues, gaining coverage is associated with large reductions (20-50%) in the incidence of cost-related non-adherence. However, even among the uninsured, only a relatively small proportion of drugs (12%) are associated with episodes of cost-related non-adherence. So, these large reductions apply to a small slice of all drugs.

These results leave open the possibility of substantive moral hazard. Although other interpretations cannot be ruled out given the nature of the data available, a few pieces of evidence point in this direction. First, the impact of gaining insurance on non-adherence is concentrated on "old" drugs, those the individual reports having taken for more than two years. New prescriptions are not differentially less likely to be associated with episodes of non-adherence. Second, there is no impact of gaining insurance on reports of side effects, a direct health outcome, and the (individual-assessed) importance of drugs to overall health. Finally, although quite speculative, the estimates on utilization and non-adherence can be taken together to form a rough lower bound estimate of moral hazard in utilization from prescription drug coverage. Of the overall 15% increase in utilization, about one-third can be attributed to moral hazard. Identifying the specific

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nature and obtaining more precise estimates of moral hazard is an important avenue for future research.

The paper is organized as follows. The next section discusses the empirical strategy, the Medicare Part D expansion, and the PDS data. Section III shows the impact of Part D on insurance coverage. Section IV gives the results on utilization. Section V discusses the findings on the incidence of cost-related non-adherence and side effects. The paper concludes with a discussion of the implications of the estimates for moral hazard and outlines some important caveats.

Part I: Empirical Strategy and Data

Let i and t index the individual and time, respectively. Then the following specification is used to examine the impact of prescription drug coverage on drug utilization:

$$(1) \qquad Y_{it} = \delta + \theta D_{it}^{AnyCoverage} + \varsigma \kappa_{it} + u_{it},$$

where Y is a dependent variable that measures utilization, and κ is a vector of control variables. The error term, u, is modeled as

$$(2) \qquad u_{it} = \gamma_t + \eta_i + v_{it},$$

where γ is a time effect, η is unobserved heterogeneity in the demand for prescription drugs, and v is white noise. The focal explanatory variable is $D^{AnyCoverage}$, which takes on a value of one if the individual had prescription drug coverage from any source and zero otherwise. The primary objective is to get consistent estimates of θ, which measures the impact of coverage on utilization. A fundamental challenge is that coverage may be correlated with the unobserved heterogeneity, rendering standard estimators, such as

Ordinary Least Squares (OLS), biased and inconsistent. The approach taken here is to use a panel fixed-effect estimator to obtain consistent estimates of θ. This requires panel data on coverage and utilization, as well as substantive temporal variation in coverage that varies across individuals in order to identify the estimate of θ. The best source of such variation is that generated by the implementation of Medicare Part D.

Medicare provides universal health insurance coverage to those age 65 and older, as well as to those on the federal disability insurance (DI) program. The original program, adopted in 1965, covered most medical needs for the elderly and disabled, including hospital and doctor costs. However, it excluded coverage for prescription drugs, which have become increasingly important over time in the treatment of common illnesses among the elderly.

Beginning in 2006, the federal government began to offer prescription drug insurance coverage to the elderly under Medicare Part D. This new Medicare benefit is delivered by private insurers under contract with the government. Beneficiaries can choose from three types of insurance plans for coverage of their drug expenditures: stand-alone plans, called Medicare Prescription Drug Plans (PDP), that just offer prescription drug benefits; Medicare Advantage (MA) plans, which are plans that provide all Medicare benefits (including prescription drugs) such as HMO, PPO, or private FFS plans; or, beneficiaries could retain their current employer/union plan, as long as it is at least as generous as (i.e., actuarially equivalent to) the standard Part D plan.

Enrollment in Part D plans was voluntary for Medicare-eligible citizens, although Medicare recipients not signed up by May 15, 2006, were subject to a financial penalty if they eventually joined the program. One group, however, was automatically enrolled:

low-income elders who had been receiving their prescription-drug coverage through state Medicaid programs (the "dual eligibles"). These dual eligibles were enrolled in Part D plans by default if they did not choose one on their own.

By now, there is a sizable literature in economics and health services research documenting the program's details and providing descriptive statistics on coverage. A number of economic studies have examined the take-up of Part D benefits, (Heiss, McFadden, and Winter, 2006; Levy and Weir, 2008), plan choice (Lucarelli and Simon, 2009; Abaluck and Gruber, 2011); and the extent Part D crowded out other private forms of prescription drug coverage (Levy and Weir, 2008; Engelhardt and Gruber, 2011). The consensus is that the Part D expansion raised prescription drug insurance coverage among the elderly by about 10 percentage points, substantially decreasing the share of the elderly without coverage. As of October, 2010, only 4.7 million, or 10% of, Medicare beneficiaries had no coverage (Kaiser, 2011).

In order to incorporate the temporal variation in coverage in the framework above, panel data are drawn from the 2005 and 2007 Prescription Drug Study (PDS), administered as a supplement to the Health and Retirement Study (HRS), a large nationally representative longitudinal survey of Americans aged 50 and older (Juster and Suzman, 1995). The core HRS surveys are administered either in person (CAPI) or by telephone (CATI) every two years in even years, and gather detailed information on demographics, income, employment, health, health insurance, and other topics relevant to the demography and economics of aging.

The PDS is an off-year supplemental mail survey commenced in 2005 and administered in odd years to roughly half (randomly chosen) of HRS respondents who

would be 65 and older in 2006 when Part D was implemented.[2] Unfortunately, the PDS was not administered to those under 65, who would have been a natural comparison group with which to assess the impact of the adoption of Part D. This means that the PDS only measures time variation in coverage, not age-by-time variation.[3] It was designed to gather information on prescription drug insurance and utilization that would be too time-consuming to gather in a CAPI/CATI interview, and was implemented specifically to provide pre- and post-data on Medicare Part D.

The PDS has two parts. The first part is a questionnaire that asks the individual generally about prescription drug insurance coverage and utilization. This included specific sources of coverage: respondent's or spouse's current or former employer or union; private market purchase (e.g., Medigap, prior to Part D); Veteran's Administration; Medicaid, Medicare HMO or Medicare Advantage; State Pharmacy Assistance Program; Medicare Part D (in 2007); or other source. It included out-of-pocket expenditure ("How much do you typically spend of your own money for a one-month supply of your regular drugs?") and utilization ("Have you used prescription drugs in the last year?"; "How many different prescription drugs did you use in the last month?"; "Of those prescription drugs, how many are ones you take on a regular basis, for example, every day or every week?"). I addition, there are questions on non-adherence commonly used in other studies: "In the past year, how often did you not fill a new prescription because of cost?" (never, 1-2 times, 3-4 times, more than 4 times); "In

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[2] That is, those administered the PDS were drawn from years of birth 1941 and earlier. The other half of HRS respondents was administered the Consumption and Activities Mail Survey (CAMS).

[3] Engelhardt and Gruber (2011) develop an instrumental variable (IV) strategy based on age-by-time variation in eligibility for Part D (i.e., above vs. below age 65, before vs. after 2006) to identify the impact of Part D on coverage, drug expenditure, and crowd-out, using pooled cross-sections from the Medical Expenditure Panel Survey (MEPS). This type of approach cannot be implemented in the PDS, for lack of data on those under 65. Despite the name of the survey, the MEPS panel data are not long enough to identify well changes from Part D with panel-data methods.

the past year, how often did you stop taking a prescription medication because of cost?" (never, 1-2 times, 3-4 times, more than 4 times); "In the past year, how often did you skip doses of a prescription medication in order to save money?" (never, 1-2 times, 3-4 times, more than 4 times).

The second part is a medication roster, for which the individual was asked to transcribe information from the labels of the ten most important prescriptions. This information included the drug name (e.g., Ciprofloxacin), the brand or trade name (Cipro) if any, the dosage (500 mg), the date filled (10/18/2005), and the dosage instructions (Take 1 capsule 3 times a day until finished).[4] In addition, the respondent was asked additional questions about each medicine: "How long have you been taking this medication?"; "How much did you pay the last time you filled the prescription?"; as well as assessments about the medication concerning expense ("It is too expensive" – strongly agree, agree, neutral, disagree, strongly disagree), importance to health ("This medication is very important for my health" – strongly agree, agree, neutral, disagree, strongly disagree), and side effects ("It often gives me unpleasant side effects" – strongly agree, agree, neutral, disagree, strongly disagree), as well as non-adherence due to cost and side effects ("In the last year, have you ever missed a dose of this medication or delayed or not filled a prescription for it?"). In the empirical analysis, these data are used to form a drug-level panel data set to examine the impact of insurance coverage on utilization and non-adherence at a far finer level than in previous studies.

Therefore, the PDS provides fairly comprehensive information at the individual and drug level for the same individuals, both before and after the implementation of Part

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[4] For those taking more than 10 medications, the individual was asked to list just the drug name for any medication beyond the tenth.

D. The analysis sample is a strongly balanced panel of 4,536 person-year observations on 2,268 individuals 65 and older. Columns 1 and 2 of Table 1 show sample means for the variables used in the empirical work for 2005 and 2007, respectively, for the individuals in the analysis sample. For comparison, columns 3-5 show the means for the same variables for all HRS individuals 65 and older for 2004, 2006, and 2008 from the HRS core survey data. Along many dimensions, the analysis and full samples are broadly comparable, with some exceptions. The rate of prescription drug coverage appears to be somewhat higher prior to 2006 in the analysis sample, with associated somewhat higher utilization and lower out-of-pocket expenditures. Analysis sample members are more likely to be married as well.

Part II: Insurance Coverage Results

The empirical analysis starts with Table 2, which examines how prescription drug insurance coverage changed between 2005 and 2007 with the expansion of Part D. This is an important first step for two reasons. First, the table illustrates the temporal change in coverage that will be central to identification in the fixed-effect estimation in the subsequent tables. Second, it allows for a comparison of estimates from the PDS, which is a newly available data source (the 2007 wave was released in March, 2011), with estimates from other data sources. In particular, the PDS ought to be able to replicate responses found in other data.

With this in mind, column 1 of Table 2 presents estimates from the following basic specification:

$$(3) \qquad\qquad D_{it}^{AnyCoverage} = \omega + \phi D_{it}^{2007} + \zeta \mathbf{\kappa}_{it} + \upsilon_{it}.$$

The primary explanatory variable is D^{2007}, which takes on a value of one if the sample year was in 2007, after Part D was implemented. The vector κ contains control variables for whether the individual was married, age, and sets of dummy variables for household income quintiles and Census division of residence, respectively; υ is a disturbance term.[5] The focal explanatory variable is $D^{AnyCoverage}$, which takes on a value of one if the individual had prescription drug coverage from any source and zero otherwise. Those sources in the PDS include respondent's or spouse's current or former employer or union, private market purchase, Veteran's Administration, Medicaid, Medicare HMO or Medicare Advantage, State Pharmacy Assistance Program, Medicare Part D (in 2007), or other source. In (3), ϕ measures the extent to which any coverage rose with the implementation of Part D (conditional on the control variables in κ). The OLS linear probability estimate in column 1 shows that such coverage rose by 10.9 percentage points. Because the sample includes person-year observations on the same individuals, the robust standard errors are clustered by individual (and shown in parentheses). This estimate of the change in coverage is very similar to what other studies in the literature have found.

Column 2 shows the related estimate from the same specification, but with the dependent variable, $D^{PublicCoverage}$, which takes on a value of one if the individual had prescription-drug coverage from a public source and zero otherwise. Following Engelhardt and Gruber (2011), "public" sources are defined as Medicaid, Medicare HMO, Medicare Advantage, State Pharmacy Assistance Program, or Medicare Part D.

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[5] Other standard controls, such as race/ethnicity, veteran status, education, etc., are time-invariant, and the parameters on which cannot be identified with the fixed-effect estimators used in the analysis. So, these variables are not included as controls.

In column 2, public coverage rose by 35.5 percentage points across the same years. The quotient of the estimates in columns 1 and 2, suggests that for every 100 individuals gaining public coverage between 2005 and 2007, only roughly 31 gained any coverage (i.e., 0.109/0.335=0.307), implying the Part D crowded out other coverage by 69%.

A direct measure of crowd-out is shown in column 3 for the following specification:

$$(4) \qquad\qquad D_{it}^{AnyCoverage} = \alpha + \beta D_{it}^{PublicCoverage} + \psi\kappa_{it} + \varepsilon_{it},$$

Where β measures the extent to which public coverage raises any coverage, and, therefore, $1-\beta$ measures crowd-out. The fixed-effect estimate shown in the bottom row of the table is $\hat{\beta} = 0.27$ and indicates 73% crowd-out. This is very similar to the instrumental variable crowd-out estimates of Engelhardt and Gruber (2011), based on data from the MEPS. They found 75% crowd-out. This gives some confidence that PDS can capture behavior found in other studies on Medicare Part D and prescription drugs.

A key assumption for identification under the fixed-effect framework is that unobserved heterogeneity is time-invariant (in levels). In particular, those who switch or obtain coverage are not systematically different from those who do not in how their demand for prescription medication evolves over time. Obviously, with only two waves of PDS data, this assumption cannot be tested directly. Instead, the bottom row of Table 2 provides a partial check on this by including in κ two variables measured in the PDS that indicate intentions to switch coverage. The first is a dummy variable that takes on a value of one if in 2005 the individual stated he/she was very likely to enroll in Part D, and zero otherwise. This "enrollment likelihood" question was asked to all individuals in 2005, even those with private prescription drug coverage. The second is a dummy

variable that takes on a value of one if the individual indicated he/she had considered in the last year switching prescription drug plans, and zero otherwise. This question was asked to all individuals in 2007. Controlling for these switching variables, the estimate of is β similar. Though not airtight, this lends at least some credibility to the central identification assumption.

Part III: Utilization Results

Changes in drug utilization from gaining coverage can be thought of along four dimensions. There are potential extensive margin changes in the share of the elderly using any prescription drugs. However, these will be expected to be small, given that almost 92% of the elderly in 2005 used prescription drugs. In addition, there are potential intensive margin responses: a) holding the number and composition of drugs taken constant, more doses can be taken[6]; b) holding the number of drugs constant, the composition could change, driven by substitution based on price (e.g., within drug, from brand toward generic, or within therapeutic class, across drugs that are therapeutically similar) or quality (e.g., toward drugs with fewer side effects); c) the number of drugs taken could change.

It should be emphasized that for each of these four dimensions, gaining coverage could reduce cost-related non-adherence or induce moral hazard. Table 3 shows estimates of the impact of prescription drug coverage on drug utilization. These estimates do not distinguish between non-adherence and moral hazard. Instead, they are simply the net impact of prescription drug coverage on utilization.

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[6] Except for reasons related to cost, it would seem this would be an unlikely channel for response, as it would be presumed that a physician would prescribe the clinically appropriate dosage for the individual's medical condition and characteristics.

The estimates are based on the specification in (1). The dependent variable in column 1 of the table is an indicator for whether the individual used any prescription drugs in the last year and measures the extensive margin. It is drawn from the questionnaire portion of the PDS. The dependent variables in columns 2 and 3 measure the intensive margin c), the number of drugs used in the last month, in total and on a regular basis (every or every week), respectively. They are drawn from the questionnaire portion of the PDS. The dependent variable in column 4 also measures the intensive margin c), but is the number of prescription drugs from the medication roster. For those with more than 10 drugs, this measure is right-censored.

The fixed-effect estimate of θ shown in column 1 indicates a 3.7 percentage point increase in utilization on the extensive margin associated with insurance coverage. This is a relatively small effect given that almost 82% of the uninsured used prescription drugs prior to the Part D expansion (in 2005), as shown in the bottom row of the table. Columns 2 and 3 show the estimates for the impact of coverage on the number of drugs taken, both in total and on a regular basis, in the last month. Here, $\hat{\theta} = 0.4$, which relative to the sample mean for the uninsured in 2005 suggests that coverage increases the number of drugs taken by about 13%. Column 4 shows the random-effects censored regression estimate for the number of prescription drugs listed on the medication roster. Based on this measure, utilization rose by 17%.

These increases in utilization are at the low end of those in the previous literature. Kaestner and Khan (2010) provide a very nice summary of these findings. In particular, Khan and Kaestner (2009) estimated a 4-10% increase in utilization from gaining coverage. Yang et al. (2006) estimated a 7% increase.

Part VI: Results on Non-Adherence

To attempt to disentangle how much of the changes in utilization from gaining coverage are related to reductions in financial constraints, Table 4 shows estimates from the following econometric model:

$$(5) \qquad\qquad D_{it}^{CRN} = \mu + \rho D_{it}^{AnyCoverage} + \xi \kappa_{it} + e_{it},$$

where D^{CRN} is a dependent variable that is one of three general measures of cost-related non-adherence (CRN) typically used in the literature and taken from the PDS questionnaire: whether any unfilled prescriptions in the last year, whether stopped taking a medication due to cost in the last year, and whether skipped doses to save money in the last year. The bottom row of the table shows that across measures, almost 20% of the uninsured experienced cost-related non-adherence in 2005. The fixed-effect estimates in the second row indicate that coverage reduces cost-related non-adherence fairly substantially, by 4-7 percentage points. Relative to the sample mean in the bottom row these represent 20-35% declines in the incidence of cost-related non-adherence.

Table 5 exploits the data from the medication roster and moves to a person-year-drug level model isomorphic to (5):

$$(6) \qquad\qquad D_{ijt}^{CRN} = \mu + \rho D_{it}^{AnyCoverage} + \xi \kappa_{it} + e_{ijt},$$

in which j indexes the drug. The key to this analysis is that the individual was asked a battery of questions about each drug separately listed on the roster. There are two questions related to non-adherence, one for cost and the other for side effects ("In the last year, have you ever missed a dose of this medication or delayed or not filled a prescription for it?"). There are 16,586 person-drug-year observations in the prescribed

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medication sample. Column 1, row1 of the table shows that 11.7% of the drugs taken by the uninsured in 2005 had associated episodes of cost-related non-adherence. This is a relatively low frequency, but only reflects drugs *taken*. It may be that the most elastic cost margin is whether to take the drug at all. This statistic also sheds little light on the marginal health benefit of the non-adhered drugs. Column 3, row1 of the table shows that 3.1% of the drugs taken by the uninsured in 2005 had associated episodes of side-effect-related non-adherence.

Columns 2 and 4 show the impact of gaining coverage on these two forms of non-adherence, with robust standard errors clustered by individual shown in parentheses. There is a 5.6 percentage point reduction in cost-related non-adherence associated with prescription drug coverage. On a base of 11.7 percentage points for the uninsured in 2005, this represents a 48% reduction in the incidence of cost-related non-adherence, a statistically significant and economically substantial effect. There is essentially no corresponding reduction in side-effect-related non-adherence.

The remaining two rows of the table provide separate estimates by the "vintage" of the drug. Here vintage refers to the length of time the individual reports having taken the drug. There are two groups. "New" drugs are drugs that have been taken for two years or less. For the 2007 wave of the PDS, this covers all drugs prescribed in 2006 and 2007, after the implementation of Part D; for the 2005 wave, this covers all drugs prescribed in 2004 and 2005.[7] Hence, "new" drugs will be those prescribed after the increase in coverage associated with the Part D expansion. This will include drugs in

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[7] Depending on the date the PDS was filled out, this two-year window could spill back into part of 2005 for those reporting in the 2007 wave, and back into 2003 for those reporting in the 2005 wave. Finer coding to align with calendar years exactly is not possible as the responses to these questions had pre-set categories that determine the look-back periods.

intensive margins b) and c) described above. Conversely, "old" drugs are those that the individual reports having taken for more than 2 years. Approximately 40% of drugs are "new" and 60% are "old"; these shares are not affected by insurance coverage (estimates not shown). Interestingly, the impact of gaining coverage on cost-related non-adherence resides almost wholly among "old" drugs. Therefore, the drugs prescribed on the margin after coverage expanded from Part D were not differentially better adhered to because of cost (sharing).

Part V: Discussion and Caveats

In summary, the empirical analysis indicates gaining prescription drug coverage results in an estimated 15% increase in drug utilization, as measured by the number of prescription drugs taken. It does not appear that all of this increase can be explained easily by the loosening of financial constraints for two reasons. First, the large estimated reductions in cost-related non-adherence (20-50%) apply to a small slice of all drugs (11%). Second, this effect is concentrated on "old" drugs. Gaining coverage does not seem to differentially impact non-adherence for new prescriptions.

These results leave open the possibility of substantive moral hazard. Although other interpretations cannot be ruled out given the nature of the data available, two pieces of evidence point in this direction. The first is quantitative in nature, based on a simple calculation using the estimates from the empirical analysis. Of all prescriptions, 40% are new drugs, and 12% of these are associated with cost-related non-adherence. Therefore, 35% of new drugs are not associated with financial constraints (i.e., 0.35=0.40*0(1-0.12)). Since the share of all drugs that are new drugs remained constant before vs. after

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2006, this, in turn, implies that 35% of the (15 percentage-point) increase in utilization from gaining coverage is not associated with financial constraints. Hence, a lower bound on moral hazard is that moral hazard represents roughly one-third of the increase in utilization from gaining coverage. There were two primary assumptions made: 1) all of the residual increase in new drug utilization not attributed to cost-related non-adherence is moral hazard; and 2) none of the increase in old drug utilization is moral hazard.

The second is qualitative in nature and is laid out in Table 6. The table shows estimates from the person-drug-year panel for a model isomorphic to (6):

(7) $$D_{ijt}^{Assessment} = \mu + \rho D_{it}^{AnyCoverage} + \xi \kappa_{it} + e_{ijt},$$

in which the dependent variable is a dummy variable that takes on a value of one if there was an affirmative assessment of the drug by the individual along, respectively, these dimensions: importance to health ("This medication is very important for my health" – strongly agree, agree, neutral, disagree, strongly disagree), side effects ("It often gives me unpleasant side effects" – strongly agree, agree, neutral, disagree, strongly disagree); and cost ("It is too expensive" – strongly agree, agree, neutral, disagree, strongly disagree). An affirmative assessment is defined as an answer of strongly agree or agree.

Column 1, row 1 of the table shows that 91% of drugs taken by the uninsured in 2005 were considered very important to health. However, new drugs (row 2) were less likely than old drugs (row 3) to be viewed as very important to health, suggesting lower benefits from newer prescriptions. Column 2, row 1 shows the estimate of ρ in (7), with robust standard errors clustered on the individual in parentheses. It is economically small and statistically insignificant, suggesting that gaining coverage is not associated with a greater incidence of medications that are central to health. This is equally true for

new and old drugs. Similarly, there are no effects of gaining coverage on assessments concerning unpleasant side effects, a direct health impact (columns 3 and 4).

Overall, the results in results in columns 1-4 suggest little link between prescription drug coverage and self-assessments of the importance of drugs taken to health. Yet at the same time, gaining coverage dramatically decreases the share of drugs considered expensive (columns 5 and 6), especially for new drugs, the ones less likely to be viewed as important to health. Although by no means a smoking gun, the increased consumption of cheaper drugs that are not seen as (differentially) very important to health or have fewer unpleasant side effects certainly is not inconsistent with moral hazard.

There are a number of caveats to these findings. First, this paper has followed the convention in much of the literature and referred to moral hazard as insurance-induced excessive utilization, measured by the total change in utilization. More formally, however, moral hazard is the substitution effect from the reduction in price (e.g., per prescription) to the individual from the insurance. The estimates in the paper are clearly picking up uncompensated responses that are a mix of income and substitution effects. Moran and Simon (2006) estimated an income elasticity of demand for prescription drugs of 1.3, suggesting there might be a substantial wedge between the uncompensated responses estimated here and the compensated responses associated with deadweight loss from moral hazard. Second, to the extent price exceeds marginal cost for some pharmaceuticals, increased utilization may be welfare improving (Frick and Chernew, 2009). Third, to the extent there is adverse selection in the market for prescription drug insurance, increases in drug utilization from gaining coverage will represent a combination of adverse selection, because sicker individuals who gain coverage on the

margin will on average take more prescriptions, and moral hazard. Finally, the welfare implications of changes in drug utilization have to be considered in the context of broader measures of non-prescription drug medical utilization, to the extent drug and non-drug care are substitutes or complements. Better identifying and estimating the welfare implications of prescription drug utilization is clearly an important avenue for future research.

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Table 1. Sample Means for Selected Variables, by Year for the Analysis and Full HRS Samples

Sample/Year:	(1) Analysis Sample	(2)	(3) All Elderly	(4)	(5)
Variable	2005	2007	2004	2006	2008
Dummy if Covered by Any Prescription Drug Insurance	0.835	0.942	0.785	0.937	0.958
Dummy if Covered by Public Prescription Drug Insurance	0.206	0.568	0.240	0.493	0.573
Dummy if Used Any Prescription Drugs in the Last Year	0.915	0.941	0.862	0.884	0.900
Total Number of Prescription Drugs in Last Month	4.078	4.617	---	---	---
Number of Prescription Drugs Used Regularly in Last Month	3.844	4.355	---	---	---
Number of Prescription Drugs from Medication Roster	3.674	3.921	---	---	---
Dummy if Any Unfilled Prescriptions in the Last Year	0.120	0.098	0.077	0.076	0.062
Dummy if Stopped Taking a Prescription Medication in the Last Year	0.096	0.072	---	---	---
Dummy if Skipped Doses to Save Money in the Last Year	0.114	0.085	---	---	---
Dummy if Any Monthly Out-of-Pocket Prescription Drug Expenditure	0.890	0.895	---	---	---
Monthly Out-of-Pocket Prescription Drug Expenditure (in 2010 $)	83	64	113	62	52
Dummy Married	0.688	0.654	0.613	0.597	0.580
Age (in months)	858	881	879	895	911
Annual Household Income (in 2010 $)	59,816	54,403	57,019	54,653	60,121
Census Division – New England	0.043	0.043	0.042	0.042	0.041
Census Division – Mid-Atlantic	0.106	0.104	0.114	0.110	0.111
Census Division – East North Central	0.174	0.171	0.172	0.171	0.169
Census Division – West North Central	0.108	0.108	0.095	0.098	0.098
Census Division – South Atlantic	0.241	0.245	0.239	0.237	0.240
Census Division – East South Central	0.069	0.068	0.066	0.070	0.069
Census Division – West South Central	0.099	0.099	0.102	0.105	0.103
Census Division – Mountain	0.043	0.044	0.054	0.054	0.056
Census Division – Pacific	0.118	0.118	0.116	0.114	0.113

Note: Each cell shows the sample mean for the variable in the row heading and the sample in the column heading. The analysis sample consists of a strongly balanced panel of 4416 person-year observations on 2208 persons 65 and older drawn from the 2004 and 2006 waves of the HRS, who responded to the 2005 and 2007 HRS Prescription Drug Survey. To facilitate

comparisons, the samples in columns 3-5 represent all elderly in the HRS for that year with the same birth years and months as individuals in the analysis sample.

Table 2. OLS and Fixed-Effect Estimates of Changes in Prescription Drug Coverage, Robust Standard Errors in Parentheses

Explanatory Variable	(1) Dummy if Covered by Any Prescription Drug Insurance	(2) Dummy if Covered by Public Prescription Drug Insurance	(3) Dummy if Covered by Any Prescription Drug Insurance
Linear Probability Model Estimates			
Dummy if 2007	0.109 (0.008)	0.355 (0.012)	---
Dummy if Covered by Public Prescription Drug Insurance	---	---	0.174 (0.009)
Fixed-Effects Estimates			
Dummy if Covered by Public Prescription Drug Insurance	---	---	0.270 (0.015)
Fixed-Effects Estimates with Controls for Switching Coverage			
Dummy if Covered by Public Prescription Drug Insurance			0.258 (0.015)

Note: Each cell in the first two rows of the table represents the parameter estimate of the impact of the explanatory variable in the first column on the outcomes shown in the other column headings. The sample consists of a strongly balanced panel of persons 65 and older drawn from the 2004 and 2006 waves of the HRS, who responded to the 2005 and 2007 HRS Prescription Drug Survey. All specifications control for marital status, age, Census division, and income quintile. Robust standard errors clustered at the individual level are shown in parentheses.

Table 3. OLS and Fixed-Effect Estimates of the Impact of Prescription Drug Coverage on Various Measures of Utilization, Robust Standard Errors in Parentheses

Explanatory Variable	(1)	(2)	(3)	(4) Medication Roster
Source:		Questionnaire		
	Used Any Prescription Drugs in the Last Year	Number of Drugs in the Last Month	Number of Drugs Taken on a Regular Basis in the Last Month	Number of Drugs
OLS Estimates				
Dummy if Covered by Prescription Drug Insurance	0.175	1.742	1.664	
	(0.021)	(0.134)	(0.128)	
Censored Regression Estimates				
Dummy if Covered by Prescription Drug Insurance				1.267
				(0.121)
Fixed-Effects Estimates				
Dummy if Covered by Prescription Drug Insurance	0.037	0.433	0.403	
	(0.015)	(0.120)	(0.110)	
Random-Effects Censored Regression Estimates				
Dummy if Covered by Prescription Drug Insurance				0.572
				(0.088)
2005 Sample Mean for the Uninsured	0.816	3.053	2.877	3.348

Note: Each cell in the first two rows of the table represents the parameter estimate of the impact of prescription drug insurance coverage on the utilization outcomes shown in the column headings. The sample consists of a strongly balanced panel of persons 65 and older drawn from the 2004 and 2006 waves of the HRS, who responded to the 2005 and 2007 HRS Prescription Drug Survey. All specifications control for marital status, age, Census division, and income quintile. Robust standard errors clustered at the individual level are shown in parentheses.

Table 4. OLS and Fixed-Effect Estimates of the Impact of Prescription Drug Coverage on Cost-Related Non-Adherence, Standard Errors in Parentheses

Explanatory Variable	(1) Any Unfilled Prescriptions in the Last Year	(2) Stop Taking a Prescription Medication Due to Cost in the Last Year	(3) Skipped Doses to Save Money in the Last Year
Linear Probability Model Estimates			
Dummy if Covered by Prescription Drug Insurance	-0.083	-0.091	-0.076
	(0.022)	(0.021)	(0.022)
Fixed-Effects Estimates			
Dummy if Covered by Prescription Drug Insurance	-0.072	-0.036	-0.046
	(0.029)	(0.027)	(0.027)
2005 Sample Mean for the Uninsured	0.198	0.190	0.194

Note: Each cell in the first two rows of the table represents the parameter estimate of the impact of prescription drug insurance coverage on the utilization outcomes shown in the column headings. The sample consists of a strongly balanced panel of persons 65 and older drawn from the 2004 and 2006 waves of the HRS, who responded to the 2005 and 2007 HRS Prescription Drug Survey and utilized prescription drugs. Thus, they are a subsample of those in Table 3. All specifications control for marital status, age, Census division, and income quintile. Robust standard errors clustered at the individual level are shown in parentheses.

Table 5. Fixed Effect Estimates of the Impact of Prescription Drug Coverage on the Incidence of Non-Adherence due to Cost and Side Effects, by Drug Vintage, Robust Standard Errors in Parentheses

Drug Vintage	(1) Non-Adherence Due to Cost	(2)	(3) Non-Adherence Due to Side Effects	(4)
	Share of Drugs in 2005, for the Uninsured	Estimated Impact of Drug Insurance Coverage	Share of Drugs in 2005, for the Uninsured	Estimated Impact of Drug Insurance Coverage
All	0.117	-0.056 (0.020)	0.031	-0.002 (0.015)
New	0.113	-0.017 (0.036)	0.038	0.037 (0.028)
Old	0.119	-0.060 (0.021)	0.026	0.002 (0.015)

Note: Each cell in the first two rows of the table represents the parameter estimate of the impact of prescription drug insurance coverage on the characteristics of the drugs shown in the column headings. The sample consists of a strongly balanced panel of persons 65 and older drawn from the 2004 and 2006 waves of the HRS, who responded to the 2005 and 2007 HRS Prescription Drug Survey and utilized prescription drugs. Thus, they are a subsample of those in Table 3. All specifications control for marital status, age, Census division, and income quintile. Robust standard errors clustered at the individual level are shown in parentheses.

Table 6. Fixed-Effect Estimates of the Impact of Prescription Drug Coverage on Assessments of Drugs Concerning Expense, Side Effects, and Importance to Health, by Drug Vintage, Robust Standard Errors in Parentheses

Drug Vintage	(1) Drug Considered Too Expensive	(2)	(3) Drug Very Important to Health	(4)	(5) Drug with Unpleasant Side Effects	(6)
	Share in 2005 for the Uninsured	Estimated Impact of Drug Insurance Coverage	Share in 2005 for the Uninsured	Estimated Impact of Drug Insurance Coverage	Share in 2005 for the Uninsured	Estimated Impact of Drug Insurance Coverage
All	0.403	-0.139 (0.025)	0.911	0.012 (0.015)	0.052	-0.002 (0.012)
New	0.500	-0.197 (0.042)	0.879	0.034 (0.035)	0.080	-0.006 (0.029)
Old	0.346	-0.098 (0.030)	0.929	0.022 (0.017)	0.035	0.016 (0.012)

Note: Each cell in the first two rows of the table represents the parameter estimate of the impact of prescription drug insurance coverage on the characteristics of the drugs shown in the column headings. The sample consists of a strongly balanced panel of 2,629 persons 65 and older drawn from the 2004 and 2006 waves of the HRS, who responded to the 2005 and 2007 HRS Prescription Drug Survey and utilized prescription drugs. Thus, they are a subsample of those in Table 3. All specifications control for marital status, age, Census division, and income quintile. Robust standard errors clustered at the individual level are shown in parentheses.