HHS Public Access

Author manuscript

Forum Health Econ Policy. Author manuscript; available in PMC 2018 December 01.

Published in final edited form as:

Forum Health Econ Policy. 2017 December ; 20(2): .

The Price Elasticity of Specialty Drug Use: Evidence from Cancer Patients in Medicare Part D

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Abstract

Specialty drugs can bring substantial benefits to patients with debilitating conditions, such as cancer, but their costs are very high. Insurers/payers have increased patient cost-sharing for specialty drugs to manage specialty drug spending. We utilized Medicare Part D plan formulary data to create the *initial price* (cost-sharing in the initial coverage phase in Part D), and estimated the total demand (both on- and off-label uses) for specialty cancer drugs among elderly Medicare Part D enrollees with no low-income subsidies (non-LIS) as a function of the initial price. We corrected for potential endogeneity associated with plan choice by instrumenting the initial price of specialty cancer drugs with the initial prices of specialty drugs in unrelated classes. We report three findings. First, we found that elderly non-LIS beneficiaries with cancer were less likely to use a Part D specialty cancer drug when the initial price was high: the overall price elasticity of specialty cancer drug spending ranged between −0.72 and −0.75. Second, the price effect in Part D specialty cancer drug use was not significant among newly diagnosed patients. Finally, we found that use of Part B-covered cancer drugs was not responsive to the Part D specialty cancer drug price. As the demand for costly specialty drugs grows, it will be important to identify clinical circumstances where specialty drugs can be valuable and ensure access to high-value treatments.

Keywords

Specialty Drug Use; Price Elasticity; Medicare Part D; Specialty Cancer Drugs

1. Introduction

Spending on specialty drugs represented 32% of total drug spending in the U.S. in 2014 and is rapidly growing. In 2014, specialty drug spending grew by 30% while traditional drug spending increased by only 6% (Express Scripts, 2015). Specialty drugs do not have a single definition but typically have at least one of the following attributes: high prices, biologic

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agents, treating debilitating conditions, and requiring special handling and delivery (Tu and Samuel, 2012). Specialty drugs can offer life-extending or substantial quality-of-life benefits to patients; however, they are much more expensive than traditional drugs and are a major driver of health care expenditures (Pyrillis, 2012; Schilling, 2012; Tu and Samuel, 2012). In response, insurers and purchasers have called for strategies to effectively manage specialty drug use and spending (American Health Insurance Plans, 2015; Tu and Samuel, 2012).

Insurance benefit design is commonly used to manage prescription drug utilization. Evidence suggests that patients' utilization of prescription drugs responds to cost-sharing (Goldman et al., 2007). Incentive-based formularies (giving patients financial incentives to use preferred drugs) are particularly effective in controlling prescription drug spending while ensuring patients' appropriate access to medications to treat common chronic conditions such as hypertension or hyperlipidemia (Nair et al., 2003; Huskamp et al., 2005). However, it is not clear whether similar approaches are as effective for specialty drugs, which often do not have generic substitutes or other therapeutic equivalents (Tu and Samuel, 2012).

Lack of substitutes reduces insurers'/purchasers' negotiating power against manufacturers, which in turn leads them to charge high patient cost-sharing for specialty drugs (Tu and Samuel, 2012). If patients do not respond to cost-sharing due to potentially significant benefits of specialty drugs, high cost-sharing would be counter-productive because it would put patients at financial risk without reducing utilization. Insurers might consider lowering cost-sharing to protect price-insensitive specialty drug users; however, this is unlikely in competitive markets because insurers are concerned about adverse selection: lower cost-sharing is likely to attract more high-risk, costly patients than their competitors (Danzon and Taylor, 2010). On the other hand, if patients' use of specialty drugs depends on prices, cost-sharing could effectively manage specialty drug use. Yet, that would require limiting patients' access to potentially beneficial drugs.

Consequently, designing benefit schemes for specialty drugs involves tough choices between ensuring patients' affordable access and constraining drug spending. To address this challenge, it is essential to know how patients' use of specialty drugs responds to drug benefit generosity. Evidence on this issue in an elderly population is limited, although the elderly are more likely than other age groups to be afflicted with conditions for which specialty drugs are used. We estimated the price elasticity of specialty drug use among elderly enrollees in Medicare Part D. We focused on specialty cancer drugs, which comprise one-third of total specialty drug spending (Herric, 2014). Specifically, we performed four analyses. First, we examined the total demand for specialty cancer drugs in Part D. Second, we analyzed specialty drug use only in leukemia patients to assess whether our estimates are sensitive to the choice of a specific cancer type versus all cancers. Third, we conducted a separate analysis for newly diagnosed patients to examine whether their price responsiveness differs from others. Finally, we explored whether use of cancer drugs covered by medical benefits (Medicare Part B) is responsive to the price of Part D specialty drugs.

Despite its significance, studying the price elasticity of specialty drug use has been difficult because drug benefit information was not readily available and drug plan choice is usually voluntary, which leads specialty drug benefits to be endogenous. This issue was not properly

addressed in most prior work. We utilized Part D plan formulary data, which became available recently in a format linkable to patient-level data, to create measures of specialty drug cost-sharing (hereafter referred to as “prices”). We addressed endogeneity associated with Part D plan choice by instrumenting the initial price of specialty cancer drugs with the initial prices of specialty drugs in unrelated classes.

2. Background

Medicare Part D plan benefits

The Medicare Part D standard benefit has three phases: initial coverage, coverage gap, and catastrophic coverage. Initial coverage has an annual deductible ($360 in 2016) and 25% coinsurance after the deductible is met. After total drug spending reaches a threshold ($3,310 in 2016), beneficiaries enter the coverage gap and pay a significant share of drug spending. In-gap cost-sharing for brand-name drugs was 100% in 2010 but decreased to 50% in 2011–2012, 47.5% in 2013–2014, and 45% in 2015–2016. It will decline 5 percentage points per year thereafter. Coinsurance for generic drugs has decreased by 7 percentage points every year since 2011. In 2020, after paying the deductible, beneficiaries will have 25% coinsurance for both generic and brand-name drugs until they reach catastrophic coverage, which kicks in with 5% coinsurance after patients’ out-of-pocket (OOP) spending reaches a threshold ($4,850 in 2016).

Many Part D plans modify the standard scheme and adopt tiered formularies for initial coverage.[1] In 2015, a majority of plans had separate two-tier schemes (preferred and non-preferred) for brand-name and generic drugs, and many plans had a separate tier for specialty drugs (MedPAC, 2015).

Part D allows plans to place specialty drugs, defined as drugs with a negotiated monthly total payment greater than $600[2], in a specialty tier, and to charge high cost-sharing (30%–33% coinsurance) as long as that is offset by lower deductibles. Plans without a specialty tier typically assign high-cost drugs to non-preferred (brand-name drug) tiers, which often have coinsurance higher than 33% (Hoadley et al., 2009). Higher coinsurance for a certain tier must be offset by lower cost-sharing in another tier or other benefit enhancements.

Due to different tier placement and coinsurance rates, the prices of specialty drugs vary across Part D plans, particularly in the initial coverage phase. For example, in 44 national PDPs, patients in the initial coverage phase paid from $35 to $285 for a specialty drug with a monthly total payment of $925 in 2009 (Hoadley et al., 2009). Our data indicated that coinsurance for Gleevec (imatinib; leukemia treatment), whose average monthly total payment was above $5,000, varied between 25% and 75% between 2010 and 2012.[3] Variation in in-gap coverage for specialty drugs is relatively small because in-gap coverage is usually limited to generic drugs. Few plans modify catastrophic coverage.

[1]A plan refers to a specific Part D benefit package of an organization within a market. An organization can offer multiple plans within markets, and it can serve multiple markets.
[2]Total payment is the sum of plan payment and patient cost-sharing.
[3]We discuss variability in cost-sharing for specialty drugs in more detail in a later section. More recent years may show less variation because Part D plans have increasingly used a specialty tier for specialty drugs.

The non-linear pricing schedule in Part D means that the current price for Part D drugs may differ from the expected future price, as patients move through the three benefit phases. Rational and forward-looking patients will incorporate the expected future prices in their consumption decisions (Jung et al., 2014). However, the case of specialty drugs in Part D is different. Most of the price variation occurs in the initial coverage phase. Thus, any measure incorporating all-phase prices (to account for non-linear pricing in Part D) simply scales up the price in the initial coverage phase (hereafter referred to as the initial price) due to small differences in cost-sharing in other phases, without affecting the elasticity estimates. Also, specialty drug users are relatively certain about future prices because they often pass through the gap and reach catastrophic coverage with the first fill(s). Further, beneficiaries facing high initial prices may not initiate needed specialty medications (Danzon and Taylor, 2010; Polinski et al. 2009), suggesting that the initial price is likely to determine their specialty drug use in Medicare Part D. Based on the arguments above, we focused on the initial price of specialty cancer drugs in Part D.

Part B-covered cancer drugs

Medicare Part B (medical benefits) covers drugs administered in clinical settings. Part B requires 20% coinsurance and a deductible if applicable, but beneficiaries can buy supplementary coverage to reduce their cost-sharing. Because cancer drugs were historically available as injectables and administered by physicians in clinical settings, they were covered by Part B. Patients may choose Part B-covered cancer drugs if the Part D price is high, although few recently developed (high-cost) cancer drugs exist in both oral and injectable formulations. Most specialty cancer drugs approved in recent years, particularly anti-neoplastic agents, are available only in oral formulations (CenterWatch, 2016). The substitution between Part B and Part D cancer drugs may thus be minimal. However, some drugs such as epoetin (treats anemia caused by chemotherapy) and filgrastim (prevents infections during chemotherapy) can be used either in clinical settings covered by Part B or self-administered and covered by Part D. We will explore the degree of the substitutability between Part B cancer drugs and Part D specialty cancer drugs.

Literature on the price elasticities of specialty drug use

A small but growing literature exists on how patients' use of specialty drugs responds to price. In a recent review of this literature, Doshi et al. (2016a) reported larger price effects for non-initiation or prescription abandonment at the pharmacy than for refills or total drug spending among users. Complementing this review, we discuss several studies that reported price elasticity estimates of specialty drug use and explain how their approaches differ from ours.

Goldman et al. (2006) estimated the total demand for specialty cancer drugs among employer-sponsored plan enrollees. "Total demand" consists of both on- and off-label drug uses, and includes all specialty cancer therapies (anti-neoplastic agents and supplementary cancer drugs such as anti-emetics). They did not distinguish drugs covered by medical or pharmacy benefits. Based on claims data, they constructed a "benefit index" for specialty drugs as the ratio of patients' actual OOP spending to total specialty drug spending. The estimated price elasticity of total demand for specialty cancer drugs was −0.10. They

attempted to address endogeneity in the benefit index for specialty drugs by using the benefit index for non-specialty drugs as an instrument. However, their instrument may be endogenous because non-specialty drugs can be complements to specialty drugs. The small price elasticities may also be due to inclusion of specialty drugs covered by medical benefits because patients may be more compliant with services offered in physicians' offices.

In a subsequent study, Goldman et al. (2010) focused on on-label specialty cancer drug use by selecting specific specialty cancer drugs and patients with cancer types for which each drug is approved. Like their previous study, they included specialty drugs covered by medical or pharmacy benefits, and they used claims data to calculate the price index as average OOP spending per fill. The price elasticities of specialty drug use ranged from −0.19 to −0.26, and price elasticities for the number of fills among users were between −0.04 and −0.11. Biased selection in plan choice was not addressed, although it may have been small in the employer-sponsored plans in their study.

Using similar data to Goldman et al. (2006; 2010), Karaca-Mandic et al. (2010) examined use of specialty Rheumatoid Arthritis (RA) drugs. Constructing separate indices for medical and pharmacy prices, they found that specialty RA drug initiation responded only to pharmacy prices (elasticity = −0.09). The price index was based on actual OOP spending from claims data, and bias due to endogenous plan choice was not addressed.

Taylor (2014) used 2007–2008 Part D data to estimate the total demand for specialty cancer drugs among Part D enrollees with four common cancers (breast, prostate, lung, and colon). She addressed selection in Part D plan choice by instrumenting the price of specialty cancer drugs with prices of drugs in different classes (RA and Multiple Sclerosis (MS)). Prices were measured by actual OOP spending from claims data. She found that a $100 price increase reduced the likelihood of specialty cancer drug use by 16% in 2007 and 35% in 2008.[4] However, some results were counter-intuitive: specialty RA/MS drug use was positively associated with price, and the price effect was significant for people with little copayment due to low-income subsidies (LIS).

Recently, Doshi et al. (2016b) examined use of specialty drugs among newly diagnosed leukemia patients in Part D. They compared specialty drug utilization between patients with low-income subsidies (LIS) and non-LIS patients. The price differences between these groups were large: the price for the first 30-day fill was $2,600 for non-LIS enrollees and < $5 for LIS enrollees. They reported that non-LIS patients were less likely to initiate specialty drug use within 6 months after diagnosis and took twice as long to fill the first prescription.

A critical issue is that previous studies all lacked drug formulary information and constructed prices from patients' *actual* OOP spending except Doshi et al. (2016b). Use of actual spending, which reflects patients' choices, can distort plan price comparisons (Table A1 presents an example of a misleading comparison). Further, most prior work did not

[4]Taylor (2014) reported descriptive data on drug prices by cancer type while estimating the marginal effects across the four common cancer types. It was not straightforward to convert the marginal effects in her study to price elasticities. We obtained the weighted average of the specialty cancer drug prices across the four cancers, which was $330 in 2007 and $218 in 2008. The elasticities based on these numbers were −0.53 in 2007 and −0.76 in 2008.

properly correct for endogenous choice of specialty drug benefits, which can lead to biased estimates. Like Taylor (2014), we used drug prices in unrelated classes as instruments, but we used plan formulary data to calculate the instruments. We estimated the model for LIS people and found they were not responsive to prices. Similar to Doshi et al. (2016b), one of our analyses examined the price responsiveness in leukemia patients, but only among (elderly) non-LIS enrollees who all face sizable cost-sharing.

3. Study Population and Data

The study population is a random sample of Medicare beneficiaries with cancer between 2010 and 2012. We focused on cancers for which specialty drugs are used: leukemia, lymphoma, breast, colon, lung, prostate, pancreatic, ovarian, endometrial, kidney, sarcoma, and skin cancer.[5] The sample was created in two steps. In the first step, we requested that the Centers for Medicare and Medicaid Services (CMS) identify all patients with those cancer types from 100% of Medicare claims. Using International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) diagnosis codes, CMS identified patients with each cancer type based on the standard algorithm it uses to create cancer indicators for Medicare beneficiaries in the CMS Chronic Condition Warehouse (CCW): having ≥1 inpatient or skilled nursing facility claim or ≥2 outpatient or carrier claims in a given year. After the cancer patients were identified, in the second step, we received data for a random sample of those patients across all study cancer types.[6] The sample included both newly-diagnosed patients (“new” patients) and patients with an ongoing condition (“existing” patients).

We restricted the analysis to cancer patients who were elderly (age ≥ 65), had Part A/B coverage, were alive, and stayed in the same stand-alone Prescription Drug Plan (PDP) for the entire year. We excluded LIS beneficiaries who have nominal cost-sharing and little variation in drug benefits. Patients in Medicare Advantage Prescription Drug Plans (MA-PD) also were excluded.

We also requested CMS to identify a random sample of Multiple Sclerosis (MS) and hepatitis C patients based on the same criteria used to select cancer patients. We received the data on this random sample. While patients with MS or hepatitis C were not included in the demand models, their data were necessary to construct the instrumental variables for the initial prices (discussed in the next section).

The primary data source was Part D Prescription Data Event (PDE) Files, which contain records on prescription drug fills by enrollees, including National Drug Code (NDC; unique drug identifier), date of fill, days supplied, and payments. PDE files are the only data that enable us to link beneficiary-level prescription drug use to Part D Plan Formulary files, which are essential to construct key study variables. We first linked PDE files to the MediSpan database (Medi-Span MED-file v.2, Wolters Kluwer Health) to identify

[5]We chose cancer types for which at least 5 specialty drugs are available for treatment in 2010.

[6]CMS provides researchers with the minimum Medicare data sets that are necessary for a proposed project. CMS provided us with data for up to one million unique beneficiaries for the project. We estimated that our data contained a 10% random sample of patients across all cancer types. While the sample was not stratified to be random by cancer type, the sample size of each cancer reflected the prevalence of that cancer type.

therapeutic classes of drugs. We then augmented PDE files with information from Plan Characteristics and Formulary Files on tier assignment and cost-sharing for each drug, as well as plan attributes. Medicare Master Beneficiary Summary Files (MBSF) provided beneficiaries' demographic characteristics, residence, and chronic condition indicators. Information on Part B-covered drug use came from Carrier files and Hospital Outpatient (OP) files. Carrier files contain records of non-institutional care (e.g., services in physician offices), and OP files include claims on provider services in hospital outpatient settings. We obtained ZIP-level income/education and county-level healthcare resource information from the 2010 American Community Survey and Area Health Resource Files, respectively. Table A2 reports descriptive data for all variables.

4. Methods

Analysis

We performed four analyses to examine the price responsiveness in specialty cancer drug use among the non-LIS elderly Part D enrollees with cancer. The first analysis included all cancers selected for the study and use of any specialty cancer drugs, not just those approved to treat the patient's cancer type. This approach is similar to Goldman et al. (2006) and Taylor (2014), which examined the total demand for specialty cancer drugs. Like those two studies, our analysis captures off-label drug use that is common in cancer treatments (Pfister, 2012) and is covered by most insurers (Howard et al., 2015).

Second, we assessed whether our estimates are sensitive to the choice of a specific cancer type versus all cancers. We selected leukemia patients because they had a relatively high rate of specialty drug use (7.9%), possibly because more specialty drugs are available to treat leukemia.

Third, we estimated the model separately for new patients and existing patients to examine whether the price responsiveness differs between the two groups. We used a one-year wash-out period to identify new patients as those who had no cancer claim in the prior calendar year (Davidoff et al., 2013). New patients are likely to be at the acute stage of the condition and thus may not consider the price in starting a new therapy. In addition, new patients are unlikely to make an endogenous plan choice. This offers us an additional test of the validity of the instrumental variables used in our analyses (discussed in a later section). We performed the analysis of new patients with and without addressing the endogeneity of plan choice, expecting the findings to be similar.

The fourth analysis assessed potential substitution between Part B and Part D drugs. Medicare Part B does not define specialty drugs, but it covers high-cost biologics and injectables, which would be categorized as specialty drugs if covered by Part D. However, there is a dearth of literature on Part B cancer drug use in relation to Part D benefits. Many frequently-used Part D specialty cancer drugs do not have injectable substitutes. However, some drugs (e.g., epoetin or filgrastim) are given by providers in clinical settings (covered by Part B) or self-administered (covered by Part D). Substitution between Part B and Part D may be easier for these drugs. We thus analyzed Part B cancer drug use separately for epoetin or filgrastim.

To check the validity of our analyses of non-LIS enrollees, we conducted a falsification test with the LIS population who had little cost-sharing. We expected this analysis to produce insignificant coefficients on the initial prices.

Identifying Part D specialty cancer drugs and Part B-covered cancer drugs

We defined Part D specialty drugs as products placed in a specialty tier by at least one plan (Government Accounting Office, 2010; Trish et al., 2014). We constructed a list of Part D specialty drugs from plan formulary files. Drugs used to treat cancer were identified from two sources: organizations supporting cancer patients or cancer research (e.g., National Cancer Institute, American Cancer Society, and breastcancer.org); and the MediSpan database, which records drug names by therapeutic class. By cross-walking the lists of specialty drugs and cancer drugs, we identified Part D specialty cancer drugs. We constructed two sets of specialty cancer drugs: 1) anti-neoplastic agents [7] or drugs accompanying chemotherapy,[8] and 2) anti-neoplastic agents only. Chemotherapy-accompanying drugs are among the top Part D specialty drugs by spending and frequency, and they are important part of cancer treatments. However, consumer demand for those accompanying drugs may differ from the primary anti-cancer treatment. We thus estimated the price-responsiveness separately for all cancer drugs and only for anti-neoplastic agents to check the sensitivity of the results.

Part B-covered cancer drugs were identified by the Healthcare Common Procedure Coding System (J-codes) in Carrier files and OP data.[9] We selected claims with both cancer diagnosis and cancer drug J-codes to exclude cases using cancer drugs for other conditions.

Construction of the initial price of Part D specialty cancer drugs

Part D plans place specialty cancer drugs in tiers with different levels of cost-sharing in the initial coverage phase. We used Goldman et al.'s (2004) approach to create the plan-level initial price for cancer drugs. We obtained each drug's total monthly spending (the sum of plan and beneficiary payments)[10] from PDE and the drug's initial-coverage coinsurance rate from each plan's formulary files. After accounting for deductible amounts when applicable, we calculated the monthly price of the drug in the initial coverage phase in the plan. We then computed a weighted average of the initial prices for all specialty cancer drugs[11], where the weight is the share of each drug's fills of the total specialty cancer drug fills in the entire sample. This process is described in detail using an example in Appendix Table A1.

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[7] This includes chemotherapy, immunotherapy, hormone therapy, and targeted therapy.

[8] Examples are anti-emetics for preventing nausea and vomiting caused by chemotherapy, epoetin for treating anemia induced by chemotherapy, and growth factors that help prevent infections during chemotherapy.

[9] Some cancer drugs may be given on an inpatient basis. However, drugs provided during a covered hospital stay are covered by Part A's prospective payment for the stay.

[10] While each Part D plan negotiates its own prices (total payments) of drugs, researchers do not have information on the plan's negotiated prices. The total plan payment of a drug was available to us only when the drug was used by the plan's enrollees. We had the total payment information for fewer than 30% of plans for most specialty cancer drugs. We thus used the average total monthly spending across all plans to calculate a plan's price.

[11] Only drugs on the plan's formulary were used to calculate the plan's price. Drugs excluded by any plan were infrequently used and thus excluding them from the plan's price had little impact. Particularly, Part D plans cover almost all antineoplastic agents, which are a "protected class" For specialty cancer drugs. Eighty percent of plans in our data covered about 80% of specialty cancer drugs. All Part D plans covered hepatitis C treatments available during the study period (peginterferon and ribavirin). Eight specialty MS drugs were available. All plans covered at least five of these drugs, and 86% of plans covered at least six.

The initial price can be larger than the pre-gap OOP threshold because the monthly total payment for some drugs is larger than the initial coverage threshold. For example, if a drug's monthly total payment is $4,000 and the drug has 30% initial-coverage coinsurance, the initial price of the drug is $1,200. While this exceeds the pre-gap OOP threshold ($1,097.50 in the standard benefit in 2016), it captures a large share of the price for the first fill of the drug because with that fill, the beneficiary hits the gap, where she is responsible for a large share of the remaining spending.[12]

Computing the initial price from plans' formulary files avoids a problem with prior research that used actual drug spending, which is influenced by drug benefits. We calculated each plan's initial price for each year and inflated all prices to 2012 dollars using the Consumer Price Index (CPI) for prescription drugs.

Empirical specification

We estimated the price elasticity of specialty cancer drug spending using two-part models: the first part was any specialty cancer drug use (yes/no); the second part was conditional spending among users. We calculated the overall price elasticity by combining the price effects in both parts. We discuss our analytic approaches for each part in turn.

Specialty drug use—We analyzed patients' price elasticity for specialty drug use (the first part of the model) by estimating:

$$Y_{ijt} = \alpha + \theta(INITIAL\ PRICE)_{jt} + YEAR_t + \rho X_{ijt} + \gamma Z_{ijt} + \varepsilon_{ijt} \quad (1)$$

Subscripts i, j, and t represent beneficiary, plan, and year. Y is a binary indicator of drug use, and *INITIAL PRICE* is the plan's initial price of specialty cancer drugs. We expect the coefficient of *INITIAL PRICE* (θ), which captures beneficiaries' price responsiveness, to be negative. *YEAR* dummies control for time-specific influences on specialty drug use that are common to the entire sample (e.g., the in-gap discounts starting in 2011). X is a vector of patient characteristics (age, gender, race, and health risk factors), Z is a vector of plan and local-area characteristics, and ε is an error term.

For patients' health-risk factors, we used indicators of eight chronic conditions that are common among cancer patients, the number of chronic conditions, the number of hospital admissions in the prior year, and the number of outpatient provider visits in the prior year. We also included the number of therapeutic classes of drugs taken by a patient in the prior year to capture the patient's diagnoses requiring prescription drug use and to control for the overall demand for prescription drugs. For plan characteristics, we used indicators for being a national firm, a plan with enhanced benefits, a plan with in-gap coverage, a plan applying utilization management tools for specialty cancer drugs, and the copayment for non-

[12]For drugs with prices higher than the initial coverage threshold, part of the price of the first fill is carried over to the gap phase. However, the in-gap cost-sharing/discount rates are the same across all plans. Hence, calculating cost-sharing rates in the gap would not add any variation to the initial price.

specialty cancer drugs. Local area characteristics were ZIP-level income and education, and county-level health care resource variables.

Conditional specialty drug spending—We estimated equation (1) with total annual spending on specialty cancer drugs among users (adjusted to 2012 dollars) as the dependent variable (the second part of the model). We expect conditional spending to be insensitive to the initial price due to catastrophic coverage in Part D.

Overall price elasticity—We calculated the overall price elasticity of specialty drug spending by combining the price effects in both parts and obtained standard errors by bootstrapping.

Endogeneity and Instrumental Variables (IVs)

Part D plan cost-sharing for specialty cancer drugs is endogenous because Part D plan choice is voluntary. Thus, enrollees using specialty drugs may choose plans with generous specialty drug benefits. The Durbin-Wu tests indicated that the initial price was endogenous in the models of specialty drug use (Table A3).[13] We thus instrumented this variable.

To construct IVs, we exploit *within-plan* variation in tier assignment and the level of cost-sharing for specialty drugs across therapeutic classes. The IVs for the price of specialty cancer drugs were the plan-level initial prices of specialty drugs in two *unrelated drug classes* – MS and hepatitis C treatments – which were chosen for three reasons: 1) MS and hepatitis C are major conditions for which specialty drugs are used; 2) drugs in those classes are not used to treat cancer; and 3) the probability of patients using both cancer drugs and MS or hepatitis C drugs is very low (correlation coefficient < 0.05). Thus, the IVs are unlikely to include expected cost-sharing for complementary drugs.

For the IVs to be valid, coverage for different therapeutic classes of specialty drugs (cancer, MS, and hepatitis C) within the same plan should be highly correlated. This is likely if a plan pursues a similar benefit scheme for all specialty drugs based on the plan's philosophy or management strategy or availability of financial resources (Tu and Samuel, 2012). This was in fact supported by the data. The correlation coefficients between the initial prices of specialty drugs of different therapeutic classes ranged from 0.68 to 0.78. In regressions, the initial prices of specialty MS and hepatitis C drugs were strong predictors of the initial price of specialty cancer drugs (F-statistics > 20; Table A3), suggesting that the IVs are valid.

While the initial prices should be highly correlated across therapeutic classes within a plan, they should also vary so that the IVs (the prices of specialty drugs used to treat MS or hepatitis C) are not a simple substitute for the cancer drug price. On average, 65% – 79% of specialty drugs in each class were placed in a specialty tier (range: 0% – 100%). The percent of drugs assigned to a specialty tier varied across classes within a plan: among plans placing

[13]We used IV methods for all analyses and elasticity calculations because the initial price was endogenous in the use analysis (first part of the two-part model) and IV methods are conceptually appropriate, although the tests indicated that price was not endogenous in the conditional spending analysis (second part of the two-part model).

all MS drugs in a specialty tier, the percent using a specialty tier for specialty cancer drugs ranged from 30% to 90%.

Another condition is that valid IVs should not directly influence use of specialty cancer drugs. This assumption cannot be tested, so we rely on economic theory: there is no theoretical or empirical justification that the demand for a good depends on prices of "unrelated" goods. We defined "unrelated" classes to exclude complementary or substitutable specialty drugs. This construction makes it unlikely for the IVs to directly influence use of specialty cancer drugs. In other words, the initial prices of specialty MS or hepatitis C drugs will not affect use of specialty cancer drugs among cancer patients without MS or hepatitis C. Berndt et al. (1995), Ilzuka and Jin (2005), and Taylor (2014) pursued similar identification strategies.

However, people in poor health generally select plans with generous benefits. If those people would likely use specialty cancer drugs, the IVs might not be valid. But, this possibility is unlikely for the following reasons. First, we removed patients with both cancer and MS or hepatitis C (0.3% of the sample). Second, we included in the model a large set of health-risk factors described earlier. After controlling for these factors, we expect any remaining health effects will be minimal. Third, the outcome in our models is specialty cancer drug use, not total drug use. For the remaining (unobserved) health risk to lead to bias, it would have to lead to greater specialty cancer drug use, which is unlikely.

It is also possible that plans with high cost-sharing for specialty drugs may apply utilization management (UM) tools that could affect use of *any* specialty drugs. This would mean that our IVs are not exogenous. To address this, we controlled for several UM variables: the numbers of specialty cancer drugs subject to prior authorization and quantity limits; and the percent of specialty drugs subject to any UM tool. We also performed over-identification tests, which all indicated that the over-identifying restrictions are valid (Table A3). While the assumption of exogenous IVs cannot be fully verified, our approach improves on prior work that did not correct for endogenous specialty drug benefits.

Estimation methods

We estimated all models using 2-stage least squares methods (2SLS) to address the endogeneity issue. For the use analysis (the first part), we also explored 2-stage residual inclusion (2SRI) to account for the binary dependent variable (Terza et al., 2008), and obtained almost the same results. For conditional spending among users (the second part), the residuals were not skewed. We thus used linear regressions (2SLS) because addressing endogeneity was straightforward with linear regressions. Standard errors were clustered within plans in all analyses.[14]

[14]We also estimated the models clustering standard errors within individual patients because some patients may be observed in multiple years in our data. Standard errors from these analyses were smaller than those from the models accounting for within-plan correlations. We reported within-plan clustering to be more conservative.

5. Results

We begin by describing the variability in coverage for specialty drugs across Part D plans. Table 1 compares the initial prices of selected specialty cancer drugs between plans placing those drugs in a specialty tier and plans assigning them to a non-specialty tier (a plan refers to a specific benefit package of an organization within a market, as defined earlier). The number of plans using a specialty tier differs by drug. For the top Part D specialty drug, Gleevec (imatinib; leukemia treatment), whose average monthly total cost was about $5,160 during the study period (2010–2012), 87% of plans used a specialty drug tier with the average coinsurance rate of about 30%. Among plans that did not place Gleevec in a specialty tier, coinsurance ranged between 25% and 75%. Similarly, 85% of plans placed Tarceva (erlotinib; lung cancer drug) in a specialty tier with the average coinsurance rate of 30%. However, we observed a slightly different pattern for Procrit (epoetin; treats anemia caused by chemotherapy): about 30% of plans placed Procrit in a non-specialty tier, and copayment was more commonly used than for other drugs.

We also examined the distribution of the initial price to check whether low or high cost-sharing plans are outliers. The interquartile range of the plan-level initial price was about $320 ($1,199 – $1,519 for any specialty cancer drugs and $1,599 – $1,912 for specialty anti-neoplastics). This suggests that variation in the initial price of specialty cancer drugs existed but it was not driven by outliers. We then looked at descriptive data on enrollment and specialty drug users by plan-level initial price (Appendix Table A4) but did not find any consistent patterns. This could mean that adverse selection may not be serious. Alternatively, the descriptive data, which do not account for other plan/patient characteristics, may not provide sufficient or meaningful information on selection.

Table 2 presents descriptive statistics for selected variables. About 1.4% of beneficiaries with cancer used any specialty cancer drug.[15] Average total annual spending (both plan and beneficiary payments) on specialty cancer drugs was $32,649 per user. Specialty cancer drug users spent $3,773 out-of-pocket on specialty cancer drugs annually, on average. About 95% of specialty cancer drug users reached the coverage gap, and 82% hit catastrophic coverage during the year. The mean plan-level initial price was $1,369 for all specialty cancer drugs and $1,743 for specialty antineoplastic agents.

The estimates of price-responsiveness are shown in Table 3. The OLS estimates were close to zero or statistically insignificant in most analyses, so we focus on the IV (2SLS) estimates. Marginal effects in the full-sample analyses indicate that the probability of using any specialty cancer drug during the year decreases by about 0.07 percentage points for a $100 increase in the initial price. This effect is not small, considering that 1.4% of beneficiaries use specialty cancer drugs: it corresponds to a 5% decrease in specialty drug use.

[15]Goldman et al. (2006) and Taylor (2014) examined the total demand for specialty cancer drugs and reported similar utilization rates. Other studies of on-label specialty cancer drug use (Goldman et al., 2010; Dusetzina et al., 2014; Doshi et al., 2016b) reported higher utilization rates among patients with a condition for which each specialty drug was approved.

The IV estimates indicate that a $100 price increase for anti-neoplastic agents would reduce the probability of using an antineoplastic agent by about 0.034 percentage points. This corresponds to a 2.8% decrease, which is smaller than the price responsiveness of all specialty cancer therapy drugs, suggesting that patients may be less sensitive to the initial price for anti-cancer drugs than supplementary drugs treating other symptoms.

The marginal effect of the initial price for leukemia patients was relatively large: the probability of using any specialty leukemia treatment decreases by 0.42 percentage points for a $100 price increase. This corresponds to a 5.8% decrease in the mean utilization rate of specialty drugs (7.9%) among leukemia patients. The analysis of anti-neoplastic drugs showed a very similar effect: a 0.40 percentage point decrease (−5.8%) in use for a $100 increase in the price of leukemia treatments.

Estimates of the price responsiveness of specialty drug spending among users were all insignificant, suggesting that beneficiaries do not respond to the initial price once they start using specialty drugs. This may be due to reaching catastrophic coverage in Part D. Patients usually meet the OOP threshold for catastrophic coverage after the first fill(s) of specialty drugs. Once they reach that benefit phase with 5% coinsurance, they do not respond to price.

Next, we converted these marginal effects to price elasticity estimates at the mean values of the initial prices (Table 4). Among all cancer patients, the IV estimates of the price elasticity of using specialty cancer drugs varied between −0.49 and −0.65. Conditional spending (among users) did not depend on price. The overall price elasticity of specialty drug spending (the combined effect of use and conditional spending) varied between −0.72 and −0.75, mostly driven by the price elasticity of the probability of using specialty cancer drugs. The initial price elasticity of specialty drug use for leukemia patients was relatively large, from −0.96 to −0.99. Similar to other analyses, conditional spending did not depend on price. The IV estimates of the overall price elasticity of specialty drug spending were imprecise.

Table 5 presents the results from the separate analyses of newly diagnosed and existing patients. All estimates for newly diagnosed patients were relatively small and insignificant, suggesting that new patients may not consider price in starting a new therapy. This may be because the acuteness of the condition requires immediate use of specialty drugs. The OLS and IV estimates were similar in the analysis of new patients.[16] This finding is consistent with the expectation that new patients do not make an endogenous plan choice, and it provides additional support for the validity of our IVs. Existing patients are more likely to use specialty cancer drugs when prices are lower.

Turning to the analysis of Part B cancer drug use, Table 6 shows that most coefficients on the Part D prices in the regression analyses were insignificant. This implies that Part B drug use is not responsive to the price of Part D specialty cancer drugs. The descriptive statistics show that 14% of patients used any Part B-covered cancer drug and 11% used any Part B chemotherapy. These rates are much higher than the corresponding rates of Part D specialty

[16]In the analysis of any cancer therapy, the IV estimate is a bit larger than the OLS estimate; however, it is very imprecise, which makes it hard to consider that the IV and OLS estimates are different.

cancer drug use (1.4% and 1.2%). This may be because cancer drugs were historically available in injectable formulations (Dusetzina and Keating, 2015). It may also be due to the prevalence of supplemental insurance among Medicare beneficiaries (Jacobson et al., 2014). With supplemental coverage, cost-sharing for Part B drugs is likely to smaller than that for Part D specialty cancer drugs for non-LIS enrollees (regardless of their Part D plan benefits). Thus, it is possible that we have not identified the marginal patient for whom differences in Part D prices would lead to substitution with Part B drugs.

We explored the substitution between Part B and Part D for two individual cancer drugs, epoetin and filgrastim, which can be given by providers or self-administered. The use rates of epoetin were 0.69% in Part B and 0.08% in Part D. The use rates for filgrastim were 0.76% in Part B and 0.06% in Part D. This indicates that 90%–92% of patients (non-LIS enrollees) using those drugs received the service in Part B – a similar pattern to the overall use of Part B cancer drugs. The regression analysis also produced similar results: the Part D initial price of epoetin or filgrastim did not have a significant effect on use of those drugs in Part B (Appendix Table A5). This indicates that beneficiaries tend to use Part B drugs over Part D specialty cancer drugs regardless of the availability of substitutes. This pattern may be due to the presence of supplemental coverage, which lowers the price of Part B drugs and thus makes variation in Part D plan benefits insignificant.

Next, we examined patterns of Part B drug use for LIS enrollees, who have lower drug prices in Part D than in Part B. LIS enrollees have about $6 copayment for a monthly fill of specialty drugs in Part D. About 85% of LIS cancer drug users used any Part B cancer drugs. Dominant use of Part B drugs in this group, despite lower prices in Part D, appears to support the limited availability of substitutable Part B and Part D cancer drugs. However, use of epoetin and filgrastim among LIS enrollees was different: between 55% and 79% of LIS users of those drugs received the drug in Part B – much lower rates than for any cancer drug use. [17] This suggests that cross-price effects between Part B and Part D drug use may be present when substitutes exist.[18] Again, it would be important to identify a marginal patient for whom the variation in Part D prices will lead to substitution.

Finally, Table 7 shows the results from falsification tests using LIS beneficiaries who should not respond to the price. The table indicates insignificant price effects for Part D specialty cancer drug use,[19] suggesting that the negative price effects reported above are not driven by unmeasured plan attributes.

[17]Many Part D LIS enrollees are eligible for Medicaid, which covers their Part B cost-sharing. But, the Part D LIS is applied to a broader population than Medicaid and thus some Part D LIS enrollees do not have coverage for Part B cost-sharing through Medicaid. We examined the data separately for patients with and without dual eligibility for Medicaid. We found Part B drug use rates were similar between the two groups and those rates were lower than those of non-LIS enrollees. This appears to suggest that LIS enrollees without dual eligibility have some supplemental coverage for Part B. It may also partially reflect the fact that patients prefer self-administering drugs at home than receiving drugs in physicians' offices when prices are similar.

[18]This finding is consistent with recent studies of specialty RA drugs (Yazdany et al., 2015; Doshi et al., 2016c). Both studies showed that non-LIS Part D enrollees tended to receive biologic RA treatments in Part B, while LIS enrollees were likely to use Part D-covered biologics for RA.

[19]The estimates from the falsification tests are imprecise, but they appear to be similar to those from the main models (Table 3). However, the falsification analysis is not meant to test whether the coefficients are different from those of the main model; the hypothesis of falsification tests is that the estimate is equal to zero (Pizer, 2016).

6. Discussion and Conclusion

We estimated the price responsiveness of specialty cancer drug use in an elderly population using Medicare Part D formulary data linked to patients' claims. We report three major findings and discuss their implications.

First, we found that elderly non-LIS Part D enrollees with cancer are responsive to the initial price of specialty cancer drugs but specialty cancer drug spending among users is not price-sensitive. This finding is consistent with the conclusion in a recent literature review (Doshi et al., 2016a). However, our estimates of the price elasticity of specialty cancer drug use are larger than the estimates in studies of employer-sponsored plans. Goldman et al. (2006) found a price elasticity of −0.10 for the total demand for specialty cancer drugs (including off-label use and chemotherapy-accompanying drugs). Our IV estimates of the price elasticity of the total demand for Part D patients are between −0.72 and −0.75.

Our estimates may differ from those in prior work for several reasons. First, prior work included specialty cancer drugs covered by either medical or pharmacy benefits, while we focused on pharmacy benefits. Medical benefits cover provider-administered specialty drugs. Patients may consider those services as necessary and thus may be more compliant (less price-responsive) to them than self-administered drugs. Also, cost-sharing for services covered by medical benefits is generally lower than cost-sharing for pharmacy benefits. Second, prior studies measured price by actual OOP spending, which distorts comparisons of plan benefits. Unlike prior work, we constructed the initial price based on plans' formulary information, which captures expected cost-sharing. Third, prior studies did not properly address potential endogeneity associated with plan choice. Our OLS estimates were small and/or insignificant. Finally, we focused only on the initial price while prior work used annual OOP spending. In Part D, annual OOP spending varies little among users because of catastrophic coverage. Thus, the initial price is likely to determine specialty drug use during the year. The current Part D benefit – with high initial cost-sharing followed by catastrophic coverage – may divide patients into two groups: those who use a specialty drug and reach catastrophic coverage; and those who do not use a specialty drug (Danzon and Taylor, 2010).

However, our finding is consistent with a recent study of Part D enrollees' use of specialty cancer drugs (Taylor, 2014). Her study showed relatively large price responsiveness of the total demand for specialty drugs for four common cancers among Part D enrollees: a $100 price increase reduced the likelihood of specialty cancer drug use by 16% in 2007 and 35% in 2008. Further, our finding was not due to the inclusion all specialty cancer drugs used to treat different cancers in the estimation as confirmed by our analysis of leukemia patients. Prior studies of specific cancer types also reported that patients were responsive to the price in specialty cancer drug use, although they did not report elasticity estimates (Engel-Nitz et al., 2012; Dusetzina et al., 2014).

These findings imply that cost-sharing could be effective in managing utilization and spending on specialty drugs. However, high cost-sharing can create access barriers to specialty drugs for patients who could receive large benefits from those treatments, and bring financial pressures to beneficiaries. This concern is growing as Part D plans

increasingly use a specialty tier for costly drugs: in 2015, almost all Part D plans assign costly drugs in most therapeutic classes to a specialty tier and charge high cost-sharing (MedPAC, 2015; Yazdany et al., 2015; Dusetzina and Keaning, 2015; Jung et al., 2016). Some have proposed to reduce financial burdens on Part D enrollees who use high-cost drugs and increase access to those drugs by capping beneficiaries' annual OOP spending on Part D drugs (MedPAC, 2016), or spreading the payment of high initial prices throughout the year (Doshi et al., 2016b). In addition, exploring mechanisms to manage rapidly rising drug "list" prices, on which patients' cost-sharing is based, would help address the challenge of ensuring patients' adequate access to needed drugs while controlling prescription drug spending.

Another finding is that the price effect was not significant among newly diagnosed patients. This appears to suggest that the price responsiveness may differ by patient group (e.g., patients at the acute stage versus those at the post-surgery management stage). However, the finding may be due to the relatively small variation in the price in our analysis. A recent study of new leukemia patients in Medicare showed that non-LIS enrollees tended to delay and not to use specialty drugs relative to LIS enrollees (Doshi et al., 2016b). As described earlier, the difference in cost-sharing between non-LIS and LIS enrollees was more than $2,500 in their study, while the interquartile range of the plan-level initial price was about $320 in our analysis of non-LIS enrollees only.

We were not able to assess the extent to which each explanation contributes to the finding, because of the lack of detailed clinical data and limited variation in price. However, this is an important topic for future research and would provide useful information in exploring benefit designs for costly drugs. If beneficiaries' price responsiveness differs by expected benefits from specialty drugs, it will be important to identify clinical circumstances where specialty drugs can be valuable and ensure access to high-value treatments. This idea of value-based schemes is increasingly used in benefit designs and is perhaps critical for costly specialty drugs.

Finally, we found that substitutability between Part B and Part D drugs was limited in cancer treatments. This is consistent with prior studies of RA and cancer drug use in the early years of Part D (Doshi et al., 2010; Davidoff et al., 2013). As discussed earlier, each specialty drug may have a unique therapeutic profile and may exist in either oral or injectable formulation, limiting the substitutability between Part B and Part D drugs. Alternatively, it may be because supplemental coverage for Part B drugs was prevalent in the Medicare population and we could not identify a marginal patient to whom variation in Part D drug price leads to substitution. The analysis of two specific drugs (epoetin and filgrastim) that are available in both Parts B and D supports this possibility.

As more costly specialty cancer drugs become available, the relation between the Part D drug price and Part B drug use should be continuously assessed. This is important given that Part B-covered drug use is dominant in cancer care but few tools are available to manage utilization of expensive drugs in Part B. This issue has been recognized in the private sector, and recent efforts have attempted to integrate medical and outpatient drug benefits by moving specialty drugs from medical benefits to pharmacy benefits or applying utilization

management tools to drugs covered by medical benefits (Tu and Samuel, 2012; AHIP, 2015). While those efforts have yet to be evaluated, Medicare could consider a similar approach. Further evidence on the substitution between Part B and Part D drugs would be informative.

In addition, substitution between Part D specialty drugs and other Part B services (e.g., office visits) also should be explored: greater use of Part D specialty drugs could lead to fewer follow-up visits for evaluation and management. This was beyond the scope of the current study, but is an important area to study as Medicare expands initiatives to improve value and efficiency in service delivery, such as Accountable Care Organizations (ACOs). Spending on Part D drugs is not currently included in calculating Medicare expenditures of ACOs, but it may need to be considered in developing/assessing new initiatives if Part D drugs and Part B services are substitutable.

Several limitations of the study should be noted. First, detailed clinical information, such as the stage of disease, which may predict specialty drug use, was not available in the PDE data. Data sets with such information (e.g., the Medicare-linked Surveillance Epidemiology and End Results (SEER) data) cannot be linked to Part D plan formulary and Plan Characteristics files. However, we controlled for chronic conditions and prior health care use, and our IV approaches addressed potential bias due to unobserved risk factors.

Second, we used expected prices for unrelated specialty drug classes as instruments for prices of specialty cancer drugs. The assumption of exogenous instruments might be violated if plans implemented unobserved management strategies that influenced specialty drug utilization.

Third, the utilization rate of specialty drugs in the study sample was quite low. The price responsiveness in our analysis was thus estimated from a very small group of elderly patients. It was also based on limited differences in utilization by price. Thus, the estimates might not be as solid and may not apply to certain patient groups who consider specialty drug use as a more practical and common treatment option. Also, the results may not generalize to drugs in other classes or to the non-elderly.

Fourth, we did not have information on whether beneficiaries received specialty cancer drugs through pharmaceutical assistance programs. Use of discount coupons and copayment assistance – the main tools of drug assistance programs – is banned in publicly subsidized programs including Medicare Part D (Ross and Kesselheim, 2013). Medicare beneficiaries could receive some assistance through charity organizations. However, they usually have to meet additional requirements (e.g., income criteria, physician confirmation or denial letter) to be eligible for such assistance. Thus, use of charities by Medicare beneficiaries is quite limited and is unlikely to have a systematic and large impact on the finding of our analysis.

Finally, the lack of data on supplemental coverage limited our understanding of the policy implications from the analysis of Part B cancer drugs. Future research using Part B price information would give a complete picture of the substitution between Part B and Part D drugs.

Despite these limitations, we provided the first estimate of the price responsiveness of specialty cancer drug use among the elderly using Part D plan formulary information. We found that elderly cancer patients respond to the initial price of specialty cancer drugs. As the demand for specialty drugs grows, it will be important to ensure patients' access to needed drugs while controlling spending.

Acknowledgments

This work is supported by NIH/NIA grant number 1R01AG047934-01, and NIH grant number R24 HD041025. No conflicts of interest exist.

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Appendices

Appendix Table A1

Comparison of plan benefits based on actual out-of-pocket (OOP) spending

	Plan A		Plan B		Plan C	
	Cost-sharing	**Quantity**	**Cost-sharing**	**Quantity**	**Cost-sharing**	**Quantity**
Drug 1 ($1500)	50% coins (=$750)		30% coins (=$450 copay)	1 fill	$100 copay	2 fills
Drug 2 ($750)	10% coins (=$75)	4 fills	30% coins (=$225 copay)	2 fills	$100 copay	
Price based on actual OOP spending						
	$75		$300		$100	
Expected price based on formulary						
	$297.75		$299.25		$100	

Note:

1. Plan benefit designs: All plans have a multi-tiered scheme in initial coverage, but the tier structure differs by plan. In all plans, enrollees enter a coverage gap when their total drug spending reaches $2,960, and hit catastrophic coverage after OOP spending of $4,500.
2. Total spending on each drug (spending by plan and enrollees): Both drugs are recommended to be filled once a month. The total spending on drug 1 is $1,500 for one month of supply, and total spending on drug 2 is $750.
3. Possible drug utilization in initial coverage given the benefit designs: Enrollees in plan A use only drug 2 while those in plan B use both drugs and enrollees in plan C use only drug 1. Taking only drug 2, enrollees in plan A hit the gap after 4 fills. Those in plan B enter the gap after 1 fill of drug 1 and 2 fills of drug 2, while

those in plan C reach the gap after 2 fills of drug 2. Once hitting the gap, everyone has the same cost-sharing – 45% of drug spending in 2015.

4. Price index in initial coverage based on actual OOP spending: $75 for plan A, and $300 for plan B, and $100 for plan C. This index captures the average monthly OOP spending.

5. Calculation of each plan's expected monthly price in initial coverage based on formulary:

   a. Obtain the price of each drug in each plan by multiplying the total spending of the drug by coinsurance for the drug imposed by the plan. For copayment, the drug price equals the copayment amount. This price is presented in parentheses.

   b. Get the weight for each drug as the share of each drug's fills in the total fills in the entire sample (using the number of fills in the entire sample addresses endogeneity related to utilization driven by the plan benefit design). The weighs are 0.33 and 0.67 for drugs 1 and 2, respectively.

   c. Multiply each drug's price in each plan (calculated in 5.a) times the weight of the drug, and sum to get the weighted average price. For example, the expected initial monthly price in plan A is calculated as $750*0.33 + $75*0.67=$297.75.

   d. For plans with a deductible (not used in the example above), deducible amounts are accounted for before copayment or coinsurance is applied. Suppose plan D has a $300 deductible followed by 30% coinsurance. For this plan, cost-sharing for drug 1 is calculated as $300 + ($1,500 − $300) *0.30 = $660 and cost-sharing for drug 2 is $435 (=$300 + ($750 − $300) *0.3).

Appendix Table A2

Descriptive statistics of variables used in analysis (N=297,710)

Variable	Mean	Standard Deviation
Expected copay for MS drugs($) *	1,001.21	160.35
Expected copay for Hep.C drugs($) *	830.76	348.77
Expected copay for non-specialty cancer drugs ($)	12.78	5.40
Enhanced coverage	0.34	0.47
In-gap coverage	0.17	0.37
National plan	0.83	0.37
% specialty drugs under any utilization management tools.	56.30	14.48
Number of specialty drugs requiring prior authorization	39.77	12.39
Number of specialty drugs requiring quantity limits	12.95	12.13
% people reaching gap	0.27	0.44
% people reaching catastrophic coverage	0.05	0.21
Age	76.59	7.17
Buy-in status	0.00	0.02
Female	0.51	0.50
White	0.95	0.22
Having diabetes	0.28	0.45
Having hypertension	0.69	0.46
Having ischemic heart disease	0.38	0.49
Having hyperlipidemia	0.59	0.49
Having depression	0.13	0.34
Having congestive heart failure	0.17	0.38
Having cataract	0.28	0.45
Having COPD	0.15	0.36
Having another cancer	0.08	0.27
Number of chronic conditions	4.36	2.54

Variable	Mean	Standard Deviation
Number of physician visits in the prior year	11.14	8.65
Number of hospital admissions in the prior year	0.33	0.79
Number of prescription drugs taken in the prior year	8.81	5.84
Income ($)	60,039.67	2,4485.1
% college educated	26.57	16.01
Medicare payment	809.87	107.49
Midwest	0.19	0.39
Northeast	0.38	0.48
West	0.16	0.37
Hospital admission/1,000	124.96	81.17
Physician supply/1,000	2.87	2.05
Hospital beds/1,000	3.31	2.74
Among Leukemia patients (N=11,429)		
Expected copay for common cancer drugs ($)	1797.65	217.10
Expected copay for common antineoplastic agents ($)	1855.88	220.09
Any specialty cancer drug use (%)	7.90	26.97
Any specialty antineoplastic agent use (%)	7.52	26.38

* Excluded instruments

Appendix Table A3

Test statistics related to the instrumental variables (IV) approaches

	Durbin-Wu Test	F-statistics in first stage	Over-identification test
All cancers			
Any specialty cancer drug use	F=4.109**	F=89.16***	X^2 = 0.129
Specialty chemotherapy use	F=2.861*	F=103.27***	X^2 = 0.142
Any specialty cancer drug spending	F=0.036	F=53.37***	X^2 = 0.620
Specialty chemotherapy spending	F=0.001	F=65.78***	X^2 = 0.623
Leukemia			
Any specialty cancer drug use	F=0.840	F=73.22***	X^2 =0.017
Specialty chemotherapy use	F=0.521	F=70.26***	X^2 =0.012
Any specialty cancer drug spending	F=1.587	F=24.09***	X^2 =1.401
Specialty chemotherapy spending	F=1.564	F=21.91***	X^2 =1.176

* p = 0.10,
** p < 0.05,
*** p < 0.01

Appendix Table A4

Enrollment and specialty cancer drug use/spending by plan-level initial price

Plan-level initial price of specialty cancer drugs	Enrollment (N)	Number of specialty cancer drug users (N, %)	Total specialty cancer drug spending per user ($)
1st quartile (>$1,519)	91,173	1,199 (1.31%)	29,796.83

Plan-level initial price of specialty cancer drugs	Enrollment (N)	Number of specialty cancer drug users (N, %)	Total specialty cancer drug spending per user ($)
2nd quartile ($1,379 – $1,519)	61,276	927 (1.51%)	34,099.52
3rd quartile ($1,199 – $1,379)	58,520	832 (1.42%)	32,882.38
4th quartile (<$1,199)	54,794	803 (1.47%)	30,999.20

Appendix Table A5

Part B-covered cancer drug use: marginal effect for a $100 increase in copayment in Part D plan price of epoetin (filgrastim)

	Part B-covered epoetin use	Part B-covered filgrastim use
All study sample (N=297,710)		
Rate of Part B-covered cancer drug use	0.69%	0.76%
Ordinary least squares (OLS)	−0.004 (0.010)	−0.004(0.010)
Two-state least squares (2SLS)	−0.018 (0.024)	−0.009(0.024)
Patients with leukemia (N=11,371)		
Rate of Part B-covered cancer drug use	2.03%	2.37%
OLS	−0.025(0.174)	0.164(0.094)*
2SLS	1.600(1.643)	0.402(0.484)

*
p < 0.10,
**
p < 0.05,
***
p < 0.01

Table 1

Monthly cost-sharing in initial coverage for selected specialty cancer drugs

	Plans placing the drug in a specialty tier				Plans placing the drug in a non-specialty tier			
	Coinsurance		Copayment		Coinsurance		Copayment	
	N	Mean (Min – Max)	N	Mean (Min – Max)	N	Mean (Min – Max)	N	Mean (Min – Max)
Imatinib (Gleevec)	2889	29.5% (25% – 33%)	4	$75 ($60 – $85)	423	30.7% (25% – 75%)	2	$30 ($30 – $30)
Erlotinib (Tarceva)	2828	29.5% (25% – 33%)	4	$75 ($60 – $85)	484	30.4% (25% – 75%)	2	$30 ($30 – $30)
Epoetin (Procrit)	2348	29.6% (25% – 33%)	0	-	527	30.0% (20% – 50%)	443	$40 ($30 – $90)
Filgrastim (Neupogen)	2869	29.5% (25% – 33%)	3	$80 ($70 – $85)	426	30.6% (25% – 75%)	20	$36 ($25–$45)

Note: Based on 2010–2012 Part D Plan Formulary File. A plan refers to a specific policy (benefit package) of an organization within a market.

Table 2

Descriptive statistics of selected variables

	Mean	Standard Deviation
Among all study sample (N=297,710)		
Any specialty cancer drug use (%)	1.43%	11.87
Specialty antineoplastic agent use (%)	1.20%	10.87
Among specialty cancer drug users (N=4,254)		
Annual specialty cancer drug spending ($)	$32,649.44	29,310.77
OOP spending on specialty cancer drugs ($)	$3,773.64	2,362.66
Reaching the gap (%)	94.61%	22.57
Reaching the catastrophic coverage (%)	82.20%	38.25
Among specialty antineoplastic agent use*rs (N=3,561)*		
Annual specialty antineoplastic agents spending ($)	$37,893.86	28,699.60
OOP spending on specialty antineoplastic drugs ($)	$4,330.22	2,094.19
Reaching the gap (%)	99.02%	9.86
Reaching the catastrophic coverage (%)	91.69%	27.61
Expected monthly copayment in initial coverage ($)[*]		
All specialty cancer therapy drugs	$1,369.42	214.18
Specialty antineoplastic agents	$1,743.38	253.62

[*] This price index represents the expected monthly copayment for the first fill(s) of the drug in initial coverage of the plan.

Table 3

Price effect on Part D specialty cancer drug use: Marginal effect for a $100 increase in copayment in initial coverage

	All specialty cancer therapy drugs	Specialty antineoplastics
All study sample (N=297,710)		
Specialty cancer drug use		
Ordinary least squares (OLS)	−0.035(0.022)*	−0.026(0.016)
IV analysis: 2-stage least squares (2SLS)	−0.068(0.029)**	−0.034(0.017)**
Specialty cancer drug spending among users	N=4,254	N=3,561
OLS	−319.55(279.31)	−146.16(225.64)
2SLS	−262.59(435.53)	−1516.71(341.91)
Patients with leukemia (N=11,371)		
Specialty cancer drug use		
OLS	−0.244(0.210)	−0.220(0.217)
2SLS	−0.423(0.233)*	−0.403(−0.222)*
Specialty cancer drug spending among users	N= 895	N=852
OLS	−466.21(387.34)	−337.20(363.15)
2SLS	450.31(917.01)	529.64(873.16)

Note: Standard errors (clustered within a plan) are in parentheses;

* $p < 0.10$,

** $p < 0.05$,

*** $p < 0.01$

Table 4

Price elasticities of Part D specialty cancer drug use and spending

	IV (2SLS) estimates		*OLS estimates*	
	Any specialty cancer drugs	**Specialty antineoplastics**	**Any specialty cancer drugs**	**Specialty antineoplastics**
All cancers				
Specialty drug use	−0.65(0.28) **	−0.49(0.24) ***	−0.34(0.21) *	−0.39(0.24)
Conditional specialty cancer drug spending among users	−0.11(0.18)	−0.07(0.16)	−0.13(0.12)	−0.07(0.11)
Overall elasticity of specialty cancer drug spending [a]	−0.75(0.39) **	−0.72(0.30) ***	−0.50(0.19) **	−0.40(0.20)
Leukemia				
Specialty drug use	−0.96(0.53) *	−0.99(0.55) *	−0.56(0.48)	−0.54(0.54)
Conditional specialty cancer drug spending among users	0.16(0.32)	0.18(0.30)	−0.16(0.13)	−0.12(0.13)
Overall elasticity of specialty cancer drug spending [a]	−0.79(0.71)	−0.78(0.64)	−0.73(0.36) **	−0.81(0.36) **

Note. IV: instrumental Variables approach; 2SLS: 2-Stage Least Squares; OLS: Ordinary Least Squares method; a: calculated combining effects in analyses of use and conditional spending among users with standard errors obtained by bootstrapping;

* $p < 0.10$,

** $p < 0.05$,

*** $p < 0.01$.

Table 5

Analysis of newly diagnosed and existing patients: Marginal effect for a $100 increase in copayment in initial coverage

	All specialty cancer therapy drugs	Specialty antineoplastics
Newly diagnosed patients [a] *(N=93,737)*		
Specialty cancer drug use		
Ordinary least squares (OLS)	−0.027(0.026)	−0.022(0.017)
IV estimates; 2-state least squares (2SLS)	−0.046(0.042)	−0.025(0.024)
Specialty cancer drug spending among users	N=1,122	N=840
OLS	272.48(604.55)	471.68(495.22)
2SLS	302.79(897.11)	218.16(784.39)
Existing patients (N=203,930)		
Specialty cancer drug use		
OLS	−0.043(0.025)*	−0.031(0.018)*
2SLS	−0.079(0.032)**	−0.053(0.021)**
Specialty cancer drug spending among users	N=3,131	N=2,721
OLS	−559.17(308.34)*	−365.91(251.75)
2SLS	−439.06(498.33)	−269.11(381.77)

[a]Newly diagnosed patients were defined as those with no cancer claim in the prior year (a one-year wash-out period). Standard errors (clustered within a plan) are in parentheses;

*p < 0.10,

**p < 0.05,

***p < 0.01

Table 6

Part B-covered cancer drug use: marginal effect for a $100 increase in copayment in Part D

	Part B-covered cancer drug	Part B-covered chemotherapy
All study sample (N=297,710)		
Rate of Part B-covered cancer drug use	13.78%	10.97%
Ordinary least squares (OLS)	−0.012 (0.046)	−0.034(0.048)
Two-state least squares (2SLS)	−0.073 (0.065)	−0.059(0.058)
Patients with leukemia (N=11,371)		
Rate of Part B-covered cancer drug use	18.32%	11.38%
OLS	0.248(0.194)	0.221(0.134)
2SLS	0.312(0.373)	0.187(0.261)

*
$p < 0.10$,

**
$p < 0.05$,

***
$p < 0.01$

Table 7

Falsification tests with Low Income Subsidy (LIS) beneficiaries: marginal effect for a $100 increase in copayment in initial coverage in Part D

	Any Part D specialty cancer drug	Part D specialty anti-neoplastics
All study LIS population (N=91,635)		
Specialty drug use		
Ordinary least squares (OLS)	−0.051(0.025)**	−0.034(0.016)*
IV estimate:2-state least square (2SLS)	−0.032(0.056)	−0.028(0.029)
Spending among users	N=3,127	N=2,167
OLS	139.222(292.47)	378.14(284.68)
2SLS	−264.57(465.25)	40.96(431.98)
LIS patients with leukemia (N= 2,575)		
Specialty drug use		
OLS	−0.140(0.201)	0.174(0.202)
2SLS	−0.516(0.411)	−0.360(0.433)
Spending among users	N=387	N=359
OLS	704.78(619.41)	575.09(570.32)
2SLS	594.17(878.41)	594.17(878.41)

OLS: Ordinary Least Squares; Standard errors (clustered within a plan) are in parentheses;

* $p < 0.10$,

** $p < 0.05$,

*** $p < 0.01$