Author/s:
Kaplan, CM;Zhang, Y

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ANTICIPATORY BEHAVIOR IN RESPONSE TO MEDICARE PART D'S COVERAGE GAP

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Abstract (199; 200 limit)

Under the standard Medicare Part D benefit structure, copayments for medications change discontinuously at certain levels of accumulative drug spending. Beneficiaries pay 25% of the cost of medications in the initial phase, 100% in the coverage gap, and 5% in the catastrophic phase. We examine whether individuals anticipate these copayment changes and adjust their consumption in advance. We use variation in birth-months of beneficiaries who enroll in Part D plans when they first turn 65. Birth-months generate exogenous variation in the end-of-year price because those who enroll earlier in the year are more likely to reach the coverage gap than those who enroll later. We study the impact of variation in end-of-year price on the first three months of medication use immediately following enrollment. We use difference-in-differences to adjust for seasonal trends in use, by comparing our main study group with those who receive low-income subsidies, and therefore do not face a coverage gap. We find strong evidence of anticipatory behavior, with an implied elasticity with respect to future prices ranging from -0.2 to -0.5. In addition, we find that beneficiaries modify their consumption by changing the quantity of prescriptions filled, instead of switching between brand-name and generic drugs.

1. Introduction

Medicare Part D, which began in 2006, provides prescription drug benefits to approximately 30 million Americans (Chronic Conditions Data Warehouse, 2013). In order to keep the new program from being prohibitively expensive (Doherty, 2004), a standard benefit was designed with several unique non-linear price features. Most notably, the standard design includes a coverage gap (or "doughnut hole") where beneficiaries pay 100% of drug costs when their accumulative annual drug spending is between $2,830 and $6,440 (2010 figures). The benefit also includes a small deductible ($250 in 2006 and $310 in 2010) and 25% coinsurance in the initial coverage phase before reaching the doughnut hole. At the other end of the doughnut hole, there is a catastrophic coverage phase with a 5% coinsurance. This benefit cycle resumes in the new calendar year. Previous studies have demonstrated that beneficiaries reduce their consumption of prescription medications following copayment increases associated with these benefit phases. For example, medication use decreases after individuals enter the Medicare Part D coverage gap (Polinski et al., 2011, Zhang et al., 2009). However, it is not well understood whether individuals anticipate the coverage gap and change their drug consumption before their actual copayment changes.

The unique benefit design features of Medicare Part D provides us an ideal setting to study how individuals respond to non-linear drug prices and whether they anticipate the price changes and adjust their behavior before the price changes. To answer these questions, we use 2007-2010 Medicare Part D data, and exploit the exogenous variation in the birthdates of individuals who enroll in Part D plans at the time they become eligible for Medicare. Regardless of which month individuals turn 65 and first enroll in Part D plans, the initial prices of medications are similar (25%

coinsurance or actuarially equivalent); however, future prices could differ substantially across individuals because their likelihood of getting into the coverage gap differs. Those born earlier in the year (e.g., January, February) are more likely to enter the coverage gap than those born in later calendar months (e.g., November, December), and therefore face a higher anticipated end-of-year price. It is also possible that those born earlier in the year are more likely to enter the catastrophic phase, which could lead to a lower anticipated future price. However, the Congressional Budget Office estimated that only 3% of all beneficiaries have spending high enough to reach the catastrophic phase (CBO, 2011), and this is likely to be lower among the youngest, healthiest beneficiaries that are the focus of this study. In order to rule out possible seasonal trends in medication use, we employ a Difference–in–Differences framework using a comparison group of beneficiaries who were newly eligible for Medicare and enrolled in Part D in the same corresponding months but did not face price changes throughout the year because they received low–income subsidies (LIS). LIS enrollees face zero or a small fixed copayments throughout the entire year rather than going through different benefit phases as non-LIS enrollees do.

Several papers in the literature examine whether individuals respond to the anticipated end-of-year price in health insurance contracts where the out-of-pocket cost varies throughout the year. Using unanticipated medical spending by dependent members of the family on a family insurance plan as an instrumental variable, Eichner (1998) estimated an elasticity with respect to future prices of -0.6. Aron-Dine et al. (2012) and Einav et al. (2013) use similar identification strategies to ours that rely on individuals who join a health insurance plan in the middle of the year. Because individuals who join a plan later in the year face the same deductibles as those who join earlier in the year, the former faces a lower probability of reaching the deductible threshold and therefore creates an exogenous variation in the end-of-year. Aron-Dine et al. (2012) estimate the elasticity with respect to future prices to be between -0.4 and -0.6. Alpert (2012) examines whether there was anticipatory behavior after the announcement of Part D, but before the implementation. In order to identify the effect of the announcement, the paper examines differences in the utilization of drugs used to treat chronic and acute conditions, because it is easier to predict drug consumption and therefore change behavior in anticipating price changes for chronic conditions than acute conditions.

Our study contributes to the existing literature in several important ways. First, our study focuses on pharmaceutical spending rather than medical spending. Drug spending is generally more predictable than medical spending, and therefore may lead to a greater degree of anticipatory behavior. Second, most other similar studies examine the effect of a deductible, where future prices are expected to be lower. The structure of Medicare Part D differs, however, in that the most relevant coinsurance rate change is the doughnut hole, which leads to an expectation that future prices might be higher. The Medicare Part D structure also facilitates our identification. Individuals who receive Low-Income Subsidies (LIS) have a low fixed copayment rate throughout the year, and do not face the various changes in out-of-pocket costs associated with the doughnut hole and other phases. This allows us to use the LIS group as a comparison group in a Difference-in-Differences specification in order to control for seasonal variation in prescription drug use. Additionally, prescription medication users primarily have two ways to modify their spending: they can change the number of prescriptions they fill, or they can switch between more expensive medications (e.g.

brand-name drugs) and less expensive medications (e.g. generic drugs). Our study examines this mechanism. Finally, Medicare Part D is a large and important program, and the policy implications are significant.

2. Methods

2.1 Main identification strategy

We study the anticipatory behavior by examining how individuals respond to differences in future prices when they face the same initial price. If individuals are forward-looking, the price that matters most is the price they pay for medications on the last day of the year (end-of-year price). This is because each additional unit purchased at the beginning of the year will simply push the number of units purchased over the whole year up by one. Thus, the additional cost of that unit over the entire year is simply equal to the end-of-year price.

We take the advantage of the exogenous variation in birth-month to study whether individuals respond to the differences in the end-of-year price when the current price is held constant, by focusing on the first three months of drug spending among individuals who just turn 65, and are thus newly eligible for Medicare. Under a standard Part D benefit structure, individuals pay a 25% coinsurance in the initial coverage phase until their accumulative annual drug spending reaches the coverage gap threshold ($2400 in 2007, $2510 in 2008, $2700 in 2009 and $2830 in 2010). Thus, all individuals face the same initial price at the beginning of their coverage following their enrollment. However, their future drug prices depend on the likelihood of them going through the different benefit phases (e.g. coverage gap and catastrophic coverage). For example, individuals who are born and enroll in Medicare Part D towards the beginning of the year are more likely to reach the doughnut hole than those who are born and enroll in the program towards the end of the year, just because the former has a longer time to accumulate total drug spending to reach the doughnut hole threshold.

2.2 Comparison Groups and Placebo Tests

One potential concern with measuring drug consumption during the first three months of enrollment is that there may be a seasonal trend in medication use. For example, Medicare patients may use more antibiotics in the winter months (Zhang et al., 2012b). In order to test the robustness of our results, we ran similar regressions for two control groups where we would not expect differences in drug utilization by birth month. First, we use a comparison group naturally built-in in Medicare consisting of newly eligible beneficiaries who turn 65 and qualify for low-income subsides (LIS). Medicare LIS beneficiaries pay zero or a small fixed copayment throughout the year (Kaiser Family Foundation, 2008). Because those who received LIS do not face different copayment phases throughout the year, differences in spending among LIS beneficiaries who enroll at different times of the year are unlikely to be due to price differences. One may argue that LIS and non-LIS may have different seasonal trends in medication use. However, previous studies have demonstrated that the seasonal patterns of medication use are not substantially different between LIS and non-LIS beneficiaries (Kaplan and Zhang, 2013, Zhang et al., 2012a). We also employ a Difference-in-Differences specification to control for potential seasonal trends using the LIS group. Secondly, we examine the impact of birth month on spending during the first three months of the year for 66-year olds who are in their second year of Medicare. During the second year of enrollment, all individuals have the same number of months to accumulate spending, so reaching the doughnut hole should not directly depend on birth month.

2.3 Data source and study sample

We obtained a 5% random sample of Medicare Part D claims from 2007 to 2010, from the US Centers for Medicare and Medicaid Services (CMS) Chronic Condition Warehouse. Since the doughnut hole began to close in 2011, we did not include data from after 2010. We identified individuals who became newly eligible for Medicare when they turned 65 and enrolled in Medicare Part D for the first time in the month of their 65th birthday or the subsequent month. We followed each beneficiary for the first three months after they enrolled in a Part D plan, and calculated total drug spending and total out-of-pocket drug spending during these three months. Because the drug benefit cycle restarts in January of the next year, we excluded beneficiaries who first enrolled in November or December to ensure that we have a three-month follow-up period for everyone.

2.4 Outcomes

We study how the future price affects individuals' current drug consumption. The current drug consumption was measured by total drug spending, number of monthly prescriptions filled (90 days supply is counted as 3), and the ratios of brand-name to total prescription counts, in the first three months after their enrollment in Part D plans. We choose the three-month window because it provides enough time to get an accurate picture of spending patterns, but it is short enough so that individuals are unlikely to have reached the doughnut hole.

2.5 End-of-Year Price

We calculate the average end-of-year price by enrollment month. This is done by observing the percentage of individuals who end the year in each benefit phase. Then, the average end-of-year coinsurance rate is calculated by assuming that those who do not reach the doughnut hole pay 25% coinsurance at the end of the year, those that end the year in the doughnut hole pay 100%, and those who reach the catastrophic phase pay 5%.

Table I presents a breakdown of which phase non-LIS beneficiaries were in at the end of the year, by enrollment month. Based on these percentages, we calculate the average end-of-year coinsurance rate by enrollment month, multiplying the proportion in each phase and the price in each phase. As expected, our calculation suggests that average prices declined with enrollment month. For those who enrolled in January, 12.75% reached the doughnut hole, while only 1.45% reached the catastrophic phase. Thus, the doughnut hole phase has a much larger impact on the average end-of-year coinsurance rate than the catastrophic phase.

[Table I is about here.]

Table I shows slightly higher enrollment in January than other months. There are two reasons for this. First, those born in January are slightly more likely to enroll in their birth month than those born at other times. Of those who enrolled within the first two months, 87% of January births enrolled in the first month compared to 83% for those born February through October. Second, those born in December are slightly more likely to wait until January to enroll. Approximately 30% of December births who enroll within two months enroll in the second month, compared to 17% for those born between February and October. More detail is shown in the Appendix Table 1.

2.6 Statistical analysis

We conduct two sets of linear regressions to examine the effect of the end-of-year price on medication utilization. First, we examine a reduced form equation, looking at the effects of enrollment quarters -- January-March, April-June, and July- October (as reference period) on the current drug consumption. Second, we replace enrollment month in the equation with the calculated average end-of-year price for each enrollment month in order to examine the effects of end-of-year price on the total drug spending in the first three months. Although Medicare beneficiaries typically enrolled in Part D the month that they turned 65, they are not required to, which raises the possibility that enrollment month may be endogenous. In order to adjust for this, we ran an additional specification that instrumented the calculated average end-of-year price with a set of dummies representing month of birth.

All regression models control for year dummies, gender, race, and Zip-Code level income and education. We do not adjust for risk score or other comorbidities, because our study population consists of new enrollees and for whom we do not have the prior year's medical claims. For new enrollees, CMS risk score software only uses enrollees' demographic variables, which are adjusted in our regression models. However, we do not expect this to bias our estimates because birth month is unlikely to be correlated with comorbidities in any systematic way.

2.7 Implied elasticities

Using the fact that the average end-of-year price for those who enrolled between January and March was 23% higher than those who enrolled between July and October (Table 1), we calculated implied elasticities for our estimates. From the first set of regressions, we calculate price elasticity by computing the percentage difference in total drug utilization for those who enroll from January to March to those who enroll from July to October, and dividing it by the percentage difference in the average imputed end-of-year price for the two groups. As a sensitivity analysis, we replace the enrollment month with the calculated end-of-year prices, and conduct a regression of total drug spending on price, and then calculate the implied elasticity using a similar approach.

3. Results

3.1 Summary of characteristics of study groups

Table II shows demographic characteristics for our study sample, separated by enrollment quarter and LIS status. Although some of these differences were statistically significant, the differences in absolute numbers were small. For example, the proportions of beneficiaries newly eligible for Medicare who were female in January-March, April-June, July-October were 59.8, 58.7, 59.3 percent (P-value=0.02), respectively. This suggests that controlling for demographic characteristics in our main specification may be important.

[Table II is about here.]

3.2 Individuals reduce drug spending in anticipating higher future prices

Table III presents results from regressions modeling the effects of enrollment quarter on current prescription drug spending. The first column shows the results for the non-LIS group. Our main finding suggests that that those who enrolled in the beginning of the year had significantly lower spending than those who enrolled towards the end of the year. Since individuals are less likely to reach the doughnut hole if they enrolled in later months, this finding provides evidence that individuals are forward-looking. The implied elasticity from this regression is -0.2.

The second column of Table III shows the results from the same specification, but for the LIS group. Since the LIS group did not face changes in price throughout the year, we did not expect differences in spending by enrollment group. The point estimates suggest that those who enrolled in the first three months of the year actually had higher spending, but these differences were not statistically significant. We cannot calculate elasticity in for this regression since LIS beneficiaries have no difference in end-of-year price associated with birthday. Column 3 of Table III displays our Difference-in-Differences estimates comparing the non-LIS group to the LIS group. The interaction term between the LIS indicator and the enrollment category representing the first three months of the year suggests a larger estimate for the difference in spending for the first three months. The implied elasticity for this regression is -0.5.

Column 4 shows results from a second placebo test which examines the impact of birth month on prescription drug utilization for 66-year olds. Similar to the results for the LIS group, 66-year olds born earlier in the year use more medications during the first three months. However, this specification is slightly different because, here, we examine spending during the first three months of the year (i.e. January, February, and March) for all 66-year olds, rather than the first three months of enrollment. Thus, the explanation for the higher utilization is likely not seasonal. It is possible that those born earlier in the year actually have more need for medications, or are in slightly worse health. This is consistent with the findings of Buckles and Hungerman (2008), who showed that those who are born in winter months are more likely to have more health conditions. Since both placebo tests seem to point in the opposite direction, perhaps due to seasonality and higher disease prevalence among those born earlier in the year, the results in column 1 appear to be robust.

Table IV presents results from the regression model estimating the effects of average end-of-year price on current drug spending. Although not a substantively different specification, these results provide a way to directly calculate the elasticity with respect to future price. Again, these results show that individuals reduce their current drug spending in anticipating higher future drug price. The implied elasticity is -0.22, which is similar to the model for non-LIS enrollees presented in Table III.

As discussed above, there are more January enrollees than other enrollees in other months, which raises some concern that the composition of the groups is slightly different. In column 2, we present the instrumental variables results using month of birth as an instrument for imputed average end-of-year price. These results do not differ substantially. Similar instrumental variables regressions were performed for the other specifications, and the results are almost identical. As an additional robustness check, we performed the same regressions limiting the sample to only those who enrolled in their month of birth instead of allowing individuals to be included if they enroll in their first or second month of eligibility, which leads to a more uniform distribution of enrollment month. The results from this specification, shown in the Appendix Table 2, are not substantially different from those presented in Table III. Finally, we ran additional specifications of all of our models excluding those who enrolled in January. Again, the results from these specifications do not alter our conclusions.

3.3 Reduced drug spending is due to fewer numbers of prescriptions filled instead of shifting from brand-name to generic drugs

In this subsection, we demonstrate the mechanism of how beneficiaries modify their spending in response to a change in the end-of-year price. Decrease in spending can be accomplished either by filling fewer prescriptions, or by switching to cheaper medications. We examine whether there was a difference in the number of prescriptions filled across enrollment quarters, and whether there was a change in the ratio of brand-name prescriptions to total prescriptions filled.

Table V presents the results of a regression with the number of monthly prescriptions filled as a dependent variable. We find that non-LIS individuals who enrolled earlier in the year filled significantly fewer prescription drugs than those who enrolled later in the year. There is also a seasonal effect in prescription drug counts that runs in the opposite direction. Thus, our difference-in-differences model displays even larger effects. We find that individuals whose birth-months are January-March filled on average 0.38 fewer prescriptions over the first three months of enrollment, compared to those whose birth-months are July- October.

[Table V is about here.]

Table VI shows the results for the ratio of brand-name prescriptions to total prescriptions. Column 1 shows that non-LIS individuals actually had a higher brand-to-total drug ratio if they enrolled in the first part of the year. However, this effect was also present for the LIS individuals, suggesting that the effect may be seasonal. Indeed, our difference-in-differences result shows that there was no shift between brand-name and generic drugs, after adjusting for seasonality. Results from Tables V and VI together suggest that reduced drug spending is because individuals reduced the number of prescriptions, instead of shifting from brand-name to generic drugs.

[Table VI is about here.]

3.4 Effects on Plan Choice

One possible concern with our specification is that people born at different times of the year may choose different plans. If, for example, later enrollees choose more generous plans, higher initial spending could be a response to the initial (lower) price of medications, rather than the future price. One of the most common types of enhanced benefits that plans can offer is some coverage in the doughnut hole. Most plans that offer this benefit cover only generic drugs, but some plans also cover brand name drugs in the doughnut hole. Table VII shows the impact of birth month on the probability of choosing a standard plan without coverage in the gap. Among 65-year-olds, there is not statistically significant difference in plan choice. However, 66-year-olds were much less likely to have a standard plan in the second year of enrollment if they were born early in the year. This could be a result of their experience during the first year, where they were more likely to enter the doughnut hole, which made them more likely to choose a plan the second year with gap coverage.

Nevertheless, it is still possible that plan choice could affect utilization. We conducted versions of the models shown in Table III adding controls for gap coverage in addition to models using plan fixed effects (Appendix Table 3), and none of these models altered the conclusions from these models. In addition, we stratified by gap coverage type in additional regressions using the same model as in Table III (Appendix Table 4). As expected, those without gap coverage had the largest reduction in spending in early months, relative to the LIS group. Those who had gap coverage for generic drugs only still had higher spending if they enrolled earlier in the year, while those with full gap coverage did not change their spending patterns significantly depending on when they enrolled. In the difference-in-differences specification, however, neither the full or generic coverage group differed significantly from the LIS group. These findings once again confirm our hypothesis that decreased consumption among earlier enrollees is due to the anticipatory effect of the coverage gap.

4. Discussion

We find strong evidence of anticipatory behavior. While the initial coinsurance rate for medications stays the same regardless of join month, the likelihood of reaching the doughnut hole is much greater for those who enroll in Medicare Part D early in the year due to their birth month. Thus, the anticipated future price is higher for those who enroll early in the year. Our results show significantly lower drug spending for beneficiaries who face a higher anticipated end-of-year price due to early enrollment. We estimate an implied elasticity with respect to the average end-of-year price ranging from -0.2 to -0.5. We note the lower drug spending is due to fewer numbers of prescriptions filled, instead of individuals switching from brand to generic drugs.

Our elasticity estimates are consistent with previous estimates of spot price elasticity (Goldman et al., 2007) and future price elasticity (Eichner, 1998, Aron-Dine et al., 2012). Our paper extends much of the literature on anticipatory behavior by showing that individuals respond to future increases in out-of-pocket costs similarly to how they respond to anticipated decreases in out-of-pocket costs.

Our results also provide similar conclusions to Einav et al. (2013), who also found that Medicare Part D beneficiaries who enroll earlier in the year have lower utilization during their first year. Our paper relies on a slightly different strategy that focuses only on the end-of-year price, whereas Einav and colleagues used a structural model, which identifies several different parameters relating to response to various current and future prices. Our study estimates the implied elasticity with respect to the future cost ranging from -0.2 to -0.5, whereas Einav and colleagues estimate implied elasticities with respect to various policy changes (rather than with respect to the future price) which range from -0.5 to -0.75. Since these elasticities take into consideration both current and future prices, it is not surprising that they are higher than the elasticities we estimated from our model. Taken together this implies that individuals are more responsive to current prices than future prices. Our paper also differs in that we conduct two falsification tests – in addition to looking 66-year-olds who were not new enrollees, we also used a difference-in-difference specification using LIS recipients who did not face the doughnut hole. Finally, we examine a mechanism of how individuals respond to changes in future prices. We find that people are more likely to reduce the number of medications they take, but not as likely to switch from brand to generic drugs.

There are some limitations with our study. First, there appears to be some differences across enrollment groups in the demographic variables, which might indicate that enrollment date is not truly exogenous. Other studies have observed that those born in the winter are more likely to be born to younger, lower income mothers, and have worse health outcomes (Buckles and Hungerman, 2008). We note that this would suggest that those born earlier in the year would actually be more likely to have higher spending on pharmaceuticals, and implies that our results could underestimate the true degree of forward looking behavior. Although we address this issue by controlling for observable characteristics, using a difference-in-differences specification, differences may remain. Our results for 66-year olds suggest that those born earlier in the year may actually be higher prescription drug utilizers, which may be because they have more severe health conditions. However, if this is true, it would suggest that our results are an underestimate of the true impact of enrollment quarter on medication use for 65-year olds. Second, we only focus on nondisabled beneficiaries who just turned 65 – this group is among the healthiest in the Medicare population. Finally, it is possible that prior insurance coverage may impact drug utilization in Medicare. If individuals are forward looking, those who are more likely to reach the doughnut hole due to their birth month might "stock up" on medications prior to joining Medicare. Additionally, those born in the earlier part of the year might "stock up" even if they were not fully forward looking if they finish the previous year in the stop-loss phase of their private plan, and then switch into Part D and enter the deductible phase. If this were true, it could partially explain lower utilization among early enrollees.

We predicted that individuals may be more able to predict future spending for pharmaceuticals than for medical care, and thus have a higher degree of elasticity with respect to future prices. However, our results suggest that the elasticity is between -0.2 and -0.5, which is similar to the elasticity of between -0.4 and -0.6 that Aron-Dine et al. (2012) found for medical spending. Our results suggest that Part D beneficiaries may be more forward looking than previous studies on Part D have implied, which may have important clinical and policy implications. For example, if individuals were purely forward looking, the doughnut hole could lead to lower adherence throughout the year, rather than causing gaps in medication use during certain parts of the year. Future research should examine whether differences in medication use that are present in the initial enrollment year persist over time.

From a policy standpoint, it is important to know whether consumers are fully optimizing over the drug price schedule and how this affects purchases. Under the current provisions of the Affordable Care Act, the doughnut hole will be gradually phased out by 2020. Starting on January 1 2011, pharmaceutical manufacturers offered consumers a 50% discount for brand name medications that consumes filled during the coverage gap. In addition, government subsidies will provide further discounts for both brand name and generic medications. These subsidies will increase slowly each year from 2011 to 2020 from 0% to 75% for generic drugs and from 0% to 25% for brand name drugs, so that consumers pay 25% of the cost of both brand name and generic medications while in the coverage gap by 2020. Thus, in the early years, the doughnut hole closure will have a much larger impact on brand name drugs. Our study suggests that to fully understand the effects of this new policy and estimate the future Medicare Part D federal costs, we need to incorporate the anticipatory effects in the calculation, because individuals may use more drugs at the beginning of the year in anticipating higher coverage as the coverage gap is closed. However, we also find that individuals are not likely to switch between brand and generic drugs. Thus, in the early years, the policy will likely have a larger impact on those who are already using brand name medications. We expect that beneficiaries who use many brand name medications will use more medications throughout the year in anticipation that reaching the doughnut hole is no longer as costly. This means that there are potentially larger increases in drug utilization across the entire year for beneficiaries who use brand drugs. Further research is needed to determine whether this is actually happening, and how any increased drug utilization affects health outcomes.

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Table I. Average End of Year Coinsurance by Enrollment Month among Beneficiaries without Low-income Subsidies

Enrollment Month	Coverage Phase at the End of Year[a]				Average End-of-Year Co-Insurance[b]
	N	Initial Coverage (%)	Doughnut Hole (%)	Catastrophic (%)	
Jan	12614	85.80%	12.75%	1.45%	0.3427
Feb	9149	88.02%	10.89%	1.09%	0.3295
Mar	9648	89.39%	9.69%	0.92%	0.3208
Apr	9864	91.14%	8.13%	0.73%	0.3095
May	9520	93.12%	6.37%	0.51%	0.2967
Jun	9763	95.17%	4.47%	0.37%	0.2828
Jul	10442	96.63%	3.06%	0.31%	0.2724
Aug	10357	97.51%	2.28%	0.21%	0.2667
Sep/Oct[c]	20041	98.63%	0.92%	0.07%	0.2567

[a] These numbers present the proportions of beneficiaries in each of coverage phase at the end of year.

[b] These numbers were calculated by multiplying the proportion of patients in each phase by the standard benefit coinsurance rate in that phase (e.g. for January, 85.8%×0.25+12.75%×1+1.45%×0.05=0.3427)

[c] September and October were combined due to cell-size reporting restrictions.

Table II. Sample Characteristics by Enrollment Month and Low-Income Subsidy Status

		Characteristics	Enrollment Month Jan-Mar	Apr-Jun	Jul-Oct	P-value
Non-LIS	Female (%)		59.77	58.69	59.31	0.02
	Race (%)	White	85.19	82.63	81.55	<.001
		Black	4.37	4.46	4.42	0.86
		Asian	2.12	2.11	2.00	0.41
		Hispanic	5.13	5.78	5.57	0.001
		Other	3.20	5.03	6.47	<.001
	Zip-code Level	High School (%)	57.44	57.26	57.19	0.009
		College (%)	25.45	25.71	25.80	0.01
		Median Household Income	$47,540	$47,890	$47,900	0.005
	Sample Size		31,411	29,147	41,038	
LIS	Female (%)		62.76	62.64	64.50	0.02
	Race (%)	White	49.49	47.70	46.51	0.001
		Black	17.70	17.29	17.65	0.79
		Asian	8.25	7.18	6.94	0.006
		Hispanic	20.28	21.16	21.00	0.40
		Other	4.28	6.62	7.90	<.001
	Zip-code Level	High School (%)	54.56	54.79	54.74	0.42
		College (%)	18.86	18.31	18.88	0.009
		Median Household Income	$37,800	$37,650	$37,840	0.77
	Sample Size		6,593	6,601	9,118	

Abbreviation: LIS = low-income subsidy

Table III. Effects of Enrollment Quarter on Prescription Drug Spending

	(1) Non-LIS	(2) LIS	(3) Difference-in-Differences	(4) Non-LIS 66-Year Olds
(Jan to Mar)	-18.92***	14.74	15.85	10.92**
	(5.41)	(15.67)	(12.42)	(5.10)
(Apr to Jun)	-2.29	13.91	13.81	13.23**
	(5.52)	(15.63)	(12.40)	(5.18)
(Jul to Oct)	-	-	-	
Non-LIS*(Jan to Mar)	-	-	-35.10***	
			(13.71)	
Non-LIS* (Apr to Jun)	-	-	-16.29	
			(13.74)	
Non-LIS * (Jul to Oct)	-	-	-	
Implied Elasticity	-0.2	-	-0.5	-
N	95,997	21,375	117,332	113,594

Each column is a separate linear regression. As shown in the table, the regressions include dummies for enrollment month period. The dummy for enrollment between July and October is excluded, and serves as a comparison group. In addition to the coefficients shown in the table, each regression controls for gender, race, and zip code level income and education. Standard errors are in parentheses. The implied elasticities shown at the bottom of the table were calculated using the estimate that average end-of-year prices were 23% higher for non-LIS beneficiaries who enrolled between January and March, as compared with those who enrolled between July and October. Column (3) presents a difference-in-difference specification comparing Non-LIS to LIS beneficiaries, while column (4) presents a placebo test using 66-year old beneficiaries.

*** = significant at 0.01, ** = significant at 0.05, * = significant at 0.10

Table IV. Effects of Average End-of-Year Price on Prescription Drug Spending

		(1)	(2)
		OLS Model	**IV Model**
End-of-Year Price		-270.19*** (74.89)	-284.31 (75.44)***
Log(Income)		31.79 (10.72)***	31.77 (10.72)***
College		0.13 (0.34)	0.13 (0.34)
High School		-1.33*** (0.37)	-1.33*** (0.37)
Female		5.90 (4.61)	5.90 (4.61)
Race			
	Black	-70.07*** (11.16)	-70.08*** (11.16)
	Hispanic	-112.02*** (11.84)	-112.05*** (11.84)
	Asian	-126.51*** (15.88)	-126.50*** (15.88)
	Other	-29.05*** (10.38)	-29.19*** (10.38)
	White	(Reference)	(Reference)
Year = 2007		7.17 (6.55)	7.16 (6.55)
Year = 2008		12.03* (6.37)	12.05* (6.37)
Year = 2009		15.44** (6.41)	15.43** (6.41)
Intercept		181.60* (106.05)	185.88* (106.09)
Implied Elasticity		-0.22	-0.23
N		95,997	95,997

This table shows a linear regression, similar to the regression in column (1) of Table III, but replaces the month dummies with the implied end-of-year price from Table I. The implied elasticity is calculated by converting the coefficient on End-of-Year price to a percentage change, using the average prescription drug spending for the overall sample. Column (1) shows the results from an Ordinary Least Squares model, while column (2) shows the results from an instrumental variables regression using month of birth dummies as instruments for imputed end-of-year price. Standard errors are in parentheses.

*** = significant at 0.01, ** = significant at 0.05, * = significant at 0.10

Table V. Effects of Enrollment Quarters on Number of Monthly Prescriptions Filled

	(1) Non-LIS	(2) LIS	(3) Difference-in-Differences	(4) Non-LIS 66-Year Olds
(Jan to Mar)	-0.27*** (0.06)	0.08 (0.16)	0.10 (0.13)	0.33*** (0.053)
(Apr to Jun)	-0.10* (0.06)	0.07 (0.16)	0.08 (0.13)	0.21*** (0.054)
(Jul to Oct)	-	-	-	
LIS*(Jan to Mar)	-	-	-0.38*** (0.15)	
LIS* (Apr to Jun)	-	-	-0.19 (0.15)	
LIS * (Jul to Oct)	-	-	-	
N	95,997	21,375	117,332	113,574

Each column is a separate linear regression. As shown in the table, the regressions include dummies for enrollment month period. The dummy for enrollment between July and October is excluded, and serves as a comparison group. In addition to the coefficients shown in the table, each regression controls for gender, race, and zip code level income and education. Standard errors are in parentheses.

*** = significant at 0.01, ** = significant at 0.05, * = significant at 0.10

Table VI. Effects of Enrollment Quarters on the Ratios of Brand-name Drug Counts to-Total Prescription Count.

	(1) Non-LIS	(2) LIS	(3) Difference-in-Differences	(4) Non-LIS 66-Year Olds
(Jan to Mar)	0.02*** (0.00)	0.03*** (0.01)	0.03*** (0.01)	0.00 (0.00)
(Apr to Jun)	0.02*** (0.00)	0.02*** (0.01)	0.02*** (0.01)	0.00 (0.00)
(Jul to Oct)	-	-	-	
LIS*(Jan to Mar)	-	-	0.00 (0.01)	
LIS* (Apr to Jun)	-	-	0.00 (0.01)	
LIS * (Jul to Oct)	-	-	-	
N	95,997	21,375	117,332	113,574

Each column is a separate linear regression. As shown in the table, the regressions include dummies for enrollment month period. The dummy for enrollment between July and October is excluded, and serves as a comparison group. In addition to the coefficients shown in the table, each regression controls for gender, race, and zip code level income and education. Standard errors are in parentheses.

*** = significant at 0.01, ** = significant at 0.05, * = significant at 0.10

Table VII. Effects of Enrollment Quarters on Choosing a Plan Without Gap Coverage

	(1) 65-year-old Non-LIS	(2) 66-year-old Non-LIS
(Jan to Mar)	-0.00320	-0.0162***
	(0.00348)	(0.00322)
(Apr to Jun)	-0.000102	-0.00819**
	(0.00356)	(0.00327)
(Jul to Oct)	-	-
Observations	88,445	105,164

Each column is a separate linear regression. As shown in the table, the regressions include dummies for enrollment month period. The dummy for enrollment between July and October is excluded, and serves as a comparison group. In addition to the coefficients shown in the table, each regression controls for gender, race, and zip code level income and education. Standard errors are in parentheses.

*** = significant at 0.01, ** = significant at 0.05, * = significant at 0.10

Appendix Table 1. Breakdown of Composition of Sample for Each Enrollment Month by Birth Month.

Enrollment Month	N	Born in the Same Month	Born in Month Before Enrollment	Born in Month After Enrollment
Jan	12614	8,956 (71.0%)	3,390 (26.9%)	268 (2.1%)
Feb	9149	7,635 (83.5%)	1,292 (14.1%)	222 (2.4%)
Mar	9648	8,168 (84.7%)	1,263 (13.1%)	217 (2.2%)
Apr	9864	8,031 (81.4%)	1,599 (16.2%)	234 (2.4%)
May	9520	8,081 (84.9%)	1,209 (12.7%)	230 (2.4%)
Jun	9763	8,256 (84.6%)	1,269 (13.0%)	238 (2.4%)
Jul	10442	8,785 (84.1%)	1,411 (13.5%)	246 (2.4%)
Aug	10357	8,754 (84.5%)	1,325 (12.8%)	278 (2.7%)
Sep/Oct [c]	20041	17,058 (84.3%)	2,748 (13.6%)	433 (2.1%)

Appendix Table 2. Effects of Enrollment Quarter on Prescription Drug Spending For Those Who Enrolled in Their Birth Month

	(1) Non-LIS	(2) LIS	(3) Difference-in-Differences
(Jan to Mar)	-20.20***	13.11	13.75
	(6.04)	(17.97)	(13.92)
(Apr to Jun)	0.84	16.46	16.36
	(6.06)	(17.82)	(13.82)
(Jul to Oct)	-	-	-
Non-LIS*(Jan to Mar)	-	-	-34.32**
			(15.37)
Non-LIS* (Apr to Jun)	-	-	-15.74
			(15.30)
Non-LIS * (Jul to Oct)	-	-	-
N	79,310	17,704	97,014

Each column is a separate linear regression. As shown in the table, the regressions include dummies for enrollment month period. The dummy for enrollment between July and October is excluded, and serves as a comparison group. In addition to the coefficients shown in the table, each regression controls for gender, race, and zip code level income and education. Standard errors are in parentheses.
*** = significant at 0.01, ** = significant at 0.05, * = significant at 0.10

Appendix Table 3. Effects of Enrollment Quarter on Prescription Drug Spending, Robustness Check by Controlling for Gap Coverage and Plan Fixed Effects.

VARIABLES	(1) 65-Year-Olds	(2) 65-Year-Olds	(3) 65-Year-Olds	(4) 66-Year-Olds	(5) 66-Year-Olds	(6) 65-Year-Olds
(Jan to Mar)	-18.81***	-16.73***	-18.35***	10.93**	11.68**	9.739*
	(5.412)	(5.257)	(5.465)	(5.100)	(5.097)	(5.040)
(Apr to Jun)	-2.402	-2.107	2.981	13.23**	9.447*	10.76**
	(5.522)	(5.383)	(5.561)	(5.177)	(5.179)	(5.108)
(Jul to Oct)	-	-	-	-	-	-
No Gap Coverage		-41.41***			-69.74***	
		(5.077)			(4.882)	
Controls for Gap Coverage	N	Y	N	N	Y	N
Plan Fixed Effects	N	N	Y	N	N	Y
Observations	95,997	88,445	95,997	113,574	105,164	113,574
Number of unique plans			3,975			4,034

Each column is a separate linear regression. As shown in the table, the regressions include dummies for enrollment quarter. The dummy for enrollment between July and October is excluded, and serves as a comparison group. In addition to the coefficients shown in the table, each regression controls for gender, race, and zip code level income and education. Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table 4. Effects of Enrollment Quarter on Prescription Drug Spending, By Coverage Type

	All Coverage Types			No Gap Coverage		Generic Only Gap Coverage		Full Gap Coverage	
	(1) Non-LIS	(2) LIS	(3) Difference-in-Differences	(4) Non-LIS	(5) Difference-in-Differences	(6) Non-LIS	(7) Difference-in-Differences	(8) Non-LIS	(9) Difference-in-Differences
(Jan to Mar)	-18.92*** (5.41)	14.74 (15.67)	15.85 (12.42)	-30.24*** (6.14)	15.50 (12.24)	26.21** (12.41)	16.98 (13.85)	12.24 (16.05)	15.25 (14.43)
(Apr to Jun)	-2.29 (5.52)	13.91 (15.63)	13.81 (12.40)	-5.74 (6.29)	13.39 (12.21)	14.28 (12.81)	15.37 (13.85)	6.24 (16.14)	14.26 (14.39)
(Jul to Oct)	-	-	-	-	-	-	-	-	-
Non-LIS*(Jan to Mar)	-	-	-35.10*** (13.71)	-	-46.21*** (14.03)	-	6.05 (20.70)	-	-4.24 (30.79)
Non-LIS* (Apr to Jun)	-	-	-16.29 (13.74)	-	-19.42 (14.11)	-	-4.47 (21.08)	-	-6.51 (30.98)
Non-LIS * (Jul to Oct)	-	-	-	-	-	-	-	-	-
N	95,997	21,375	117,732	65,660	87,035	16,841	38,216	5,944	27,319

Each column is a separate linear regression. As shown in the table, the regressions include dummies for enrollment quarter. The dummy for enrollment between July and October is excluded, and serves as a comparison group. In addition to the coefficients shown in the table, each regression controls for gender, race, and zip code level income and education. All difference-in-difference regressions use all 21,375 LIS enrollees as the comparison group. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Cameron M. Kaplan[1] and Yuting Zhang[2]*

Author information:
[1]University of Tennessee Health Science Center
[2]Department of Health Policy and Management, University of Pittsburgh

*Correspondence to: University of Pittsburgh, Department of Health Policy & Management, 130 DeSoto Street, A664 Crabtree Hall, Pittsburgh, PA 15261, USA. E-mail: ytzhang@pitt.edu. Tel. 412-383-5340, Fax. 412-624-3146

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