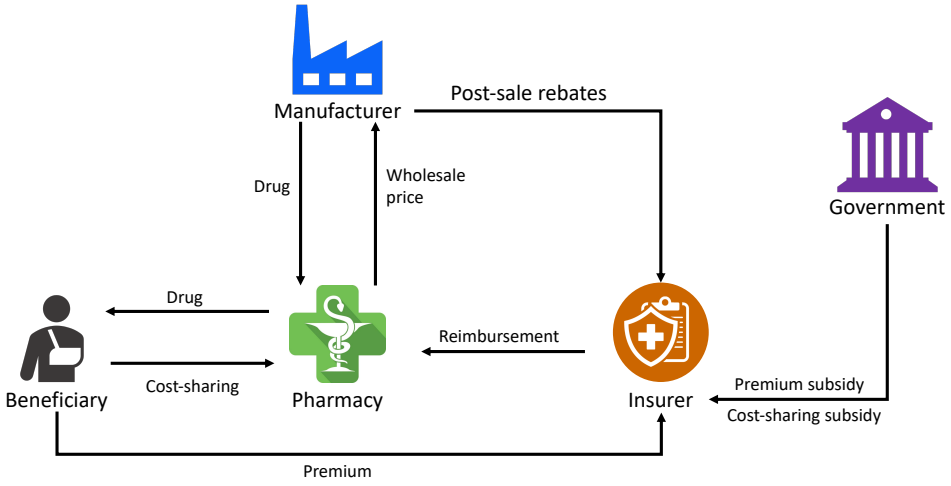
Online Appendix

The Effect of Public Insurance Design on Pharmaceutical Prices: Evidence from Medicare Part D

Katja Hofmann and Zong Huang

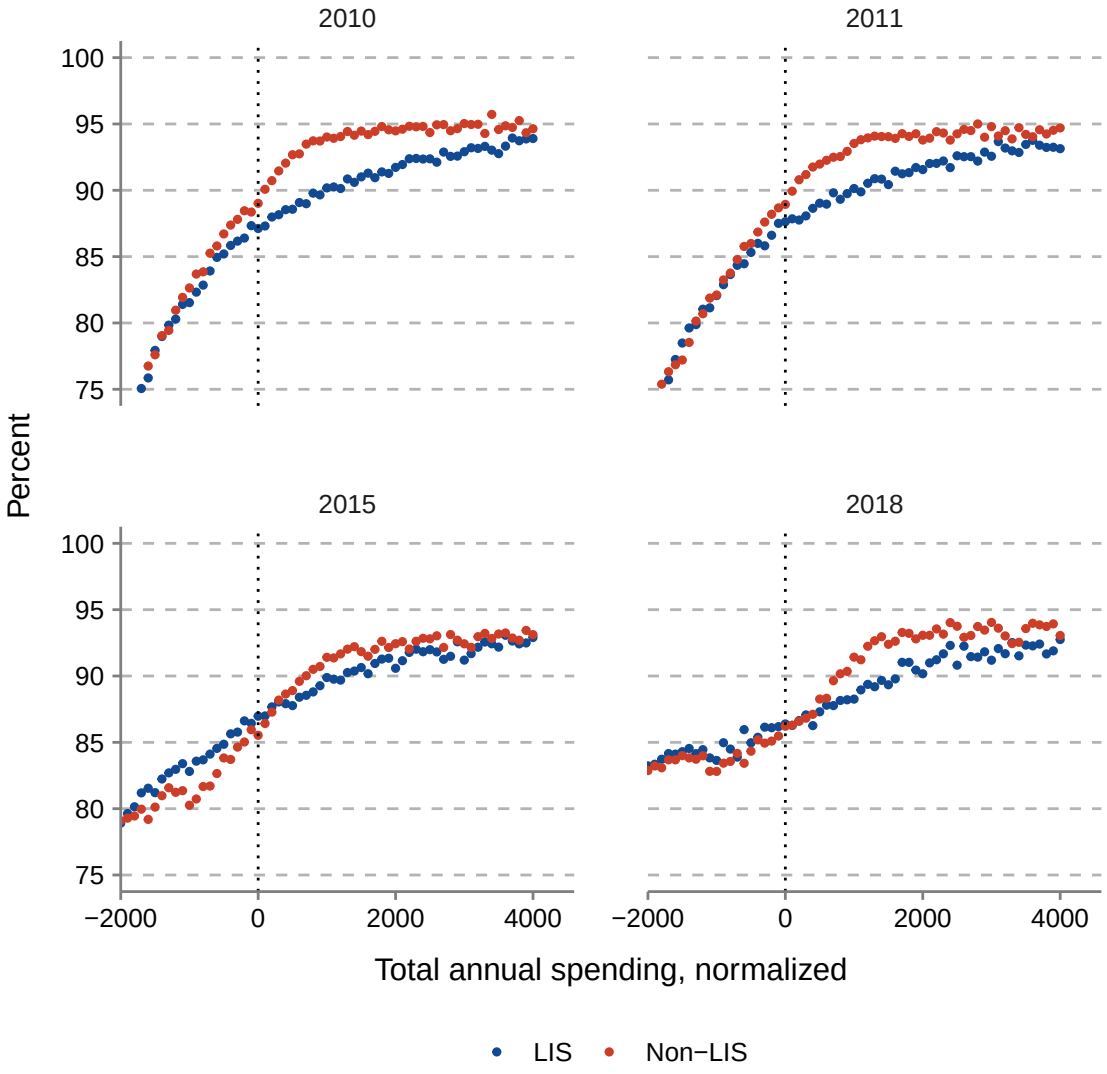
A: Additional figures

Appendix Figure A1: Drug supply chain



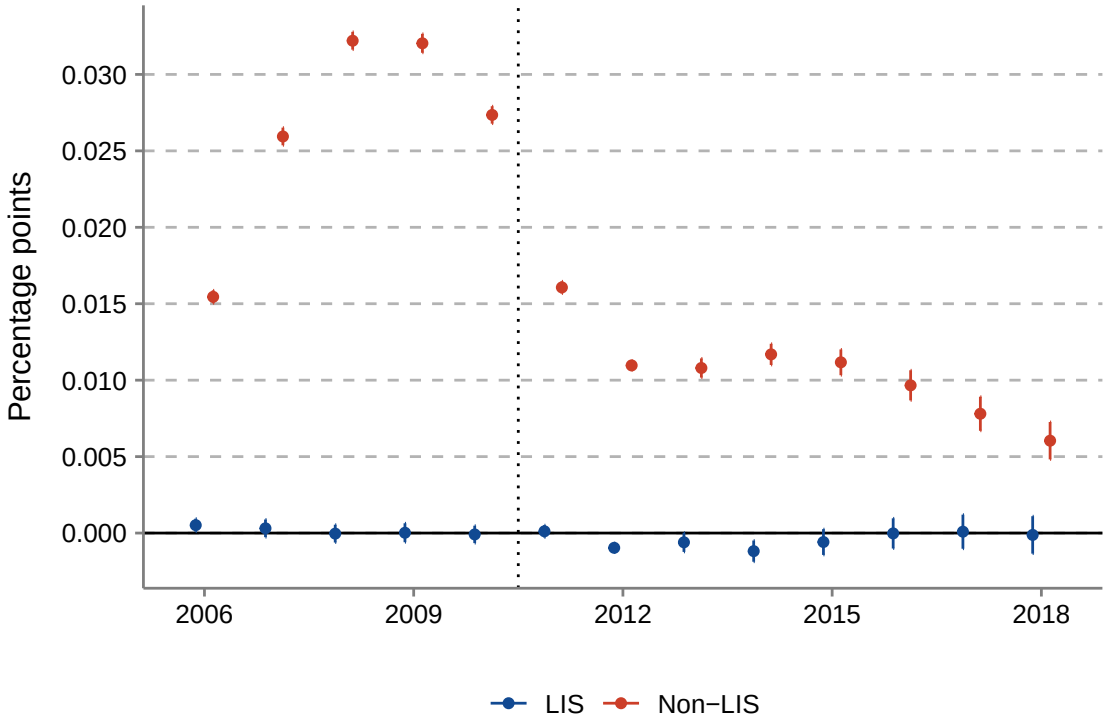
Note: This figure illustrates a simplified version of the supply chain in Medicare Part D. The illustration is based on an industry report by the Drug Channels Institute (2020).

Appendix Figure A2: Propensity of prescription drug purchase in January by annual drug spending



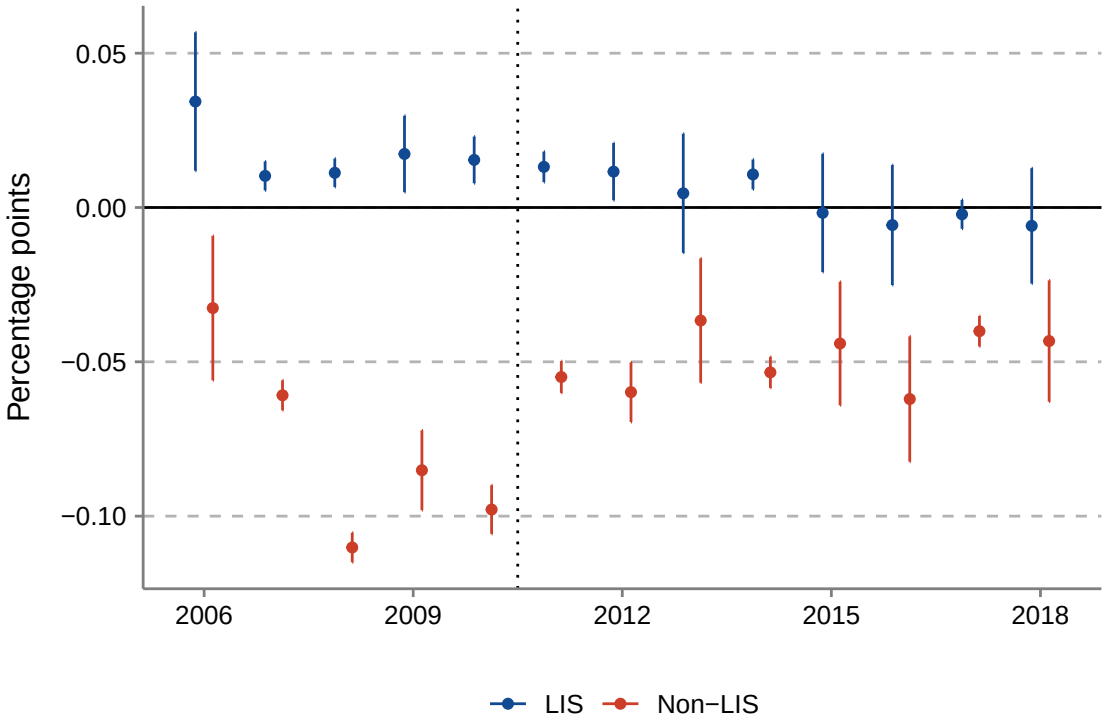
Note: Figure shows the beneficiary-level propensity of any prescription drug purchase in January as a function of total annual drug spending in 2010, 2011, 2015, and 2018, separately for non-LIS and LIS beneficiaries. Spending is normalized relative to the initial coverage limit of the respective year which marks the start of the coverage gap. The initial coverage limit was $2,830 in 2010, $2,840 in 2011, $2,960 in 2015, and $3,750 in 2018.

Appendix Figure A3: Estimates of excess bunching around start of coverage gap



Note: Figure shows the estimated excess mass near the coverage gap threshold (i.e., within $200 of the threshold) from 2006 to 2018. To quantify the amount of excess mass, we fit a cubic approximation to the empirical distribution function for non-LIS beneficiaries (shown in Figure 3), using only beneficiaries whose spending is between $1,000 and $10,000 and not near the coverage gap threshold (at least $200 away from the threshold).

Appendix Figure A4: Estimates of missing mass in December purchase propensity around start of coverage gap



Note: Figure shows the estimated dip (in percentage points) in the propensity of a December prescription drug purchase around the coverage gap threshold (i.e., within $100 of the threshold) from 2006 to 2018. To quantify the dip in the purchase propensity, we impute a cubic approximation to the conditional probability distribution for non-LIS beneficiaries (shown in Figure 4) using Equation 2. We only use beneficiaries whose spending is between $1,000 and $10,000, and exclude non-LIS beneficiaries whose spending is near the coverage gap threshold (i.e., within $200 of the threshold).

B: Additional tables

Appendix Table A1: Percent of spending, days' supply, and claims for brand-name drugs in analysis sample

Year	Spending		Days' supply		Claims	
	Total	Branded	Total	Branded	Total	Branded
2006	73.7	92.5	41.9	93.7	39.5	92.7
2007	74.7	94.6	37.7	95.7	35.9	95.2
2008	74.4	96.9	32.6	98.1	31.6	97.8
2009	75.1	98.5	30.1	99.3	29.4	99.1
2010	75.7	99.0	26.9	99.7	26.6	99.6
2011	74.6	97.6	24.0	99.3	23.8	99.1
2012	69.0	94.2	19.0	98.0	19.4	97.6
2013	64.5	89.1	15.1	95.0	16.0	94.4
2014	57.6	77.3	12.9	90.3	13.8	89.2
2015	50.9	66.5	10.7	84.1	11.7	82.9
2016	46.6	60.3	8.9	77.2	9.8	75.8
2017	41.5	53.8	7.1	69.1	8.1	68.0
2018	35.7	45.6	6.0	61.1	7.0	59.7

Note: Table shows, by year, the percent of total/brand-name Part D spending, days' supply, and number of claims accounted for by the brand-name drugs in our analysis sample.

Appendix Table A2: Event study, exposure indicator, baseline specification and robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	Group-year FE	Balanced panel	Matched NDA	Simple exposure	Without generic	With generic	Stays on patent	Loses patent
$\mathbb{1}\{2006\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.022	0.012	0.011	0.006	0.023	0.035	0.021	0.003	0.010
	(0.021)	(0.018)	(0.022)	(0.021)	(0.021)	(0.048)	(0.018)	(0.034)	(0.024)
$\mathbb{1}\{2007\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.003	-0.001	-0.008	-0.006	0.003	0.010	0.014	-0.019	0.008
	(0.016)	(0.014)	(0.017)	(0.016)	(0.016)	(0.037)	(0.014)	(0.024)	(0.017)
$\mathbb{1}\{2008\} \times \mathbb{1}\{gap\ share > Q_1\}$	-0.006	-0.003	-0.014	-0.014	-0.009	-0.004	0.003	-0.025	0.001
	(0.011)	(0.010)	(0.013)	(0.011)	(0.012)	(0.025)	(0.010)	(0.017)	(0.012)
$\mathbb{1}\{2009\} \times \mathbb{1}\{gap\ share > Q_1\}$	-0.000	-0.000	-0.007	-0.003	-0.002	0.003	0.003	-0.007	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.013)	(0.006)	(0.009)	(0.006)
$\mathbb{1}\{2010\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
$\mathbb{1}\{2011\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.017***	0.010	0.011*	0.021***	0.016***	0.019*	0.009	0.032***	0.006
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.011)	(0.006)	(0.007)	(0.009)
$\mathbb{1}\{2012\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.043***	0.031***	0.031***	0.049***	0.042***	0.046***	0.032***	0.058***	0.035**
	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)	(0.016)	(0.010)	(0.012)	(0.014)
$\mathbb{1}\{2013\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.078***	0.074***	0.067***	0.084***	0.076***	0.089***	0.053***	0.095***	0.066***
	(0.013)	(0.014)	(0.015)	(0.014)	(0.014)	(0.020)	(0.014)	(0.019)	(0.017)
$\mathbb{1}\{2014\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.120***	0.113***	0.107***	0.124***	0.117***	0.120***	0.096***	0.114***	0.143***
	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.027)	(0.025)	(0.027)	(0.029)
$\mathbb{1}\{2015\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.151***	0.131***	0.143***	0.155***	0.149***	0.144***	0.125***	0.143***	0.184***
	(0.025)	(0.023)	(0.027)	(0.026)	(0.025)	(0.032)	(0.032)	(0.033)	(0.039)
$\mathbb{1}\{2016\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.169***	0.157***	0.154***	0.172***	0.168***	0.156***	0.141***	0.167***	0.187***
	(0.028)	(0.027)	(0.031)	(0.030)	(0.028)	(0.035)	(0.036)	(0.036)	(0.053)
$\mathbb{1}\{2017\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.179***	0.168***	0.169***	0.182***	0.181***	0.162***	0.146***	0.178***	0.192***
	(0.031)	(0.027)	(0.034)	(0.033)	(0.031)	(0.035)	(0.041)	(0.039)	(0.058)
$\mathbb{1}\{2018\} \times \mathbb{1}\{gap\ share > Q_1\}$	0.188***	0.186***	0.171***	0.191***	0.188***	0.178***	0.142***	0.202***	0.166**
	(0.034)	(0.030)	(0.038)	(0.036)	(0.034)	(0.035)	(0.048)	(0.039)	(0.071)
Q_1	4.32	4.32	4.66	4.34	2.70	4.32	4.32	4.32	4.32
R^2	0.982	0.985	0.982	0.981	0.982	0.989	0.974	0.984	0.972
N (drug-market-years)	356,446	356,446	178,366	316,712	356,446	118,755	237,691	149,600	153,276

Note: Table summarizes estimation results of our event study with *exposure indicator*. All specifications include drug-market, market-year, and patent expiration year-year fixed effects. Column (1) reports the results of our baseline specification. Column (2) adds therapeutic group × year fixed effects to the baseline specification. Column (3) reports our baseline specification estimated on a balanced panel of drug-market-years. Column (4) reports our baseline specification estimated on the subset of drugs successfully linked to a New Drug Application (NDA) number. Column (5) reports our baseline specification using a simplified exposure measure that does not subtract government-financed spending from total drug-market revenue in 2010. Column (6) reports our baseline specification estimated on the subset of drugs that never experience entry of a generic alternative during our sample period. Column (7) reports our baseline specification estimated on the subset of drugs with a generic alternative. Column (8) reports our baseline specification estimated on the subset of drugs that are patent-protected throughout our sample period. Column (9) reports our baseline specification estimated on the subset of drugs that lose patent protection during our sample period. In estimation, we weight each observation by its drug-market revenue in 2010. Standard errors, in parentheses, are clustered at the drug level. N denotes the unweighted number of observations (drug-market-years). * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Appendix Table A3: Event study, linear exposure effect, baseline specification and robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	Group-year FE	Balanced panel	Matched NDA	Simple exposure	Without generic	With generic	Stays on patent	Loses patent
$\mathbb{1}\{2006\} \times$ *gap share*	-0.001	0.000	-0.001	-0.002	-0.001	0.002	-0.002	-0.002	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)
$\mathbb{1}\{2007\} \times$ *gap share*	-0.001	-0.001	-0.002	-0.002	-0.002	-0.001	-0.001	-0.003	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)
$\mathbb{1}\{2008\} \times$ *gap share*	-0.001	-0.000	-0.002*	-0.002*	-0.002	-0.001	-0.002*	-0.003**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
$\mathbb{1}\{2009\} \times$ *gap share*	-0.000	-0.000	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathbb{1}\{2010\} \times$ *gap share*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
$\mathbb{1}\{2011\} \times$ *gap share*	0.001	-0.000	0.001	0.001*	0.001*	0.002**	0.000	0.002**	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathbb{1}\{2012\} \times$ *gap share*	0.002***	0.001	0.002**	0.003***	0.003***	0.004***	0.002**	0.003***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\mathbb{1}\{2013\} \times$ *gap share*	0.006***	0.005***	0.006***	0.006***	0.008***	0.008***	0.006***	0.007***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
$\mathbb{1}\{2014\} \times$ *gap share*	0.009***	0.008***	0.010***	0.010***	0.013***	0.011***	0.009***	0.009***	0.010***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
$\mathbb{1}\{2015\} \times$ *gap share*	0.013***	0.010***	0.013***	0.013***	0.017***	0.013***	0.013***	0.012***	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)
$\mathbb{1}\{2016\} \times$ *gap share*	0.012***	0.010***	0.011***	0.013***	0.017***	0.014***	0.011**	0.014***	0.010*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)
$\mathbb{1}\{2017\} \times$ *gap share*	0.014***	0.012***	0.013***	0.014***	0.019***	0.014***	0.012**	0.015***	0.011**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)
$\mathbb{1}\{2018\} \times$ *gap share*	0.015***	0.014***	0.012***	0.015***	0.020***	0.016***	0.011*	0.017***	0.008
	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.006)	(0.004)	(0.007)
R^2	0.982	0.985	0.981	0.981	0.982	0.989	0.974	0.984	0.971
N (drug-market-years)	356,446	356,446	178,366	316,712	356,446	118,755	237,691	149,600	153,276

Note: Table summarizes estimation results of our event study with *linear exposure effect*. All specifications include drug-market, market-year, and patent expiration year-year fixed effects. Column (1) reports the results of our baseline specification. Column (2) adds therapeutic group × year fixed effects to the baseline specification. Column (3) reports our baseline specification estimated on a balanced panel of drug-market-years. Column (4) reports our baseline specification estimated on the subset of drugs successfully linked to a New Drug Application (NDA) number. Column (5) reports our baseline specification using a simplified exposure measure that does not subtract government-financed spending from total drug-market revenue in 2010. Column (6) reports our baseline specification estimated on the subset of drugs that never experience entry of a generic alternative during our sample period. Column (7) reports our baseline specification estimated on the subset of drugs with a generic alternative. Column (8) reports our baseline specification estimated on the subset of drugs that are patent-protected throughout our sample period. Column (9) reports our baseline specification estimated on the subset of drugs that lose patent protection during our sample period. In estimation, we weight each observation by its drug-market revenue in 2010. Standard errors, in parentheses, are clustered at the drug level. N denotes the unweighted number of observations (drug-market-years). * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

C: Sample construction

This section details the construction of our analysis samples.

1. Administrative Medicare Part D beneficiaries and claims data: Our sample of Part D beneficiaries is derived from a 20% random sample of the Medicare population from 2006-2018. We select all individuals enrolled in a Part D standalone prescription drug plan. Thus, we exclude Medicare-Advantage, employer-sponsored, and PACE plans—the latter two plan types are not required to report benefit package information. We measure an individual's plan and cost-sharing group (LIS or non-LIS) in December of a given year. We group together LIS beneficiaries receiving partial or full premium and cost-sharing support. We identify all prescriptions filled by an individual in our sample and exclude claims for drugs not covered by the plan. The final sample comprises 8.2 million beneficiaries, 48 million beneficiary-years, and close to 1.9 billion claims for 74,765 unique NDC codes. This dataset is used to analyze the beneficiary response to the closing of the coverage gap in Section IV.

2. Drug characteristics from Merative MarketScan® Redbook: We combine the Part D claims data with the Merative MarketScan® Redbook, which contains NDC-level information on brand status, form, route of administration, therapeutic group, and the product name given by the manufacturer. Importantly, the Redbook also contains a variable that identifies all NDCs describing pharmaceutically equivalent products, meaning products that contain the same active ingredient(s), are of the same dosage form and route of administration, and are identical in strength or concentration. We successfully merge 94.9% (70,953) of all NDCs from the Part D data, which account for more than 99.9% of Part D revenue.

3. National Drug Code Directory, Drugs@FDA, and Orange Book: We obtained historical versions of NDC Directory, Drugs@FDA, and the Orange Book for the years 2006-2018 from the Wayback Machine, Howison, Lawless, and Ucles (2018), and Williams (n.d.). The NDC Directory lists the universe of drug products, at the NDC level, for sale in the U.S. Importantly, it links NDC codes to the FDA-registered drug application number. The Drugs@FDA database includes information in the universe of drugs approved for human use in the U.S., such as application type (e.g., New Drug Application, Biologics License Application, or Abbreviated New Drug Application) and drug approval year. Lastly, the Electronic Orange Book contains patent and marketing exclusivity expiration dates for drugs that were ever granted such a right. We combine these three data sources, which allows linkage from NDC codes to patent and marketing expiration dates.

D: Manufacturer response to increased beneficiary demand

In Section IV, we find that beneficiaries became less likely to forgo prescriptions upon reaching the donut hole after the closure of the coverage gap. This implies that beneficiaries increased their demand for prescription drugs, in line with the policy change expanding insurance coverage. Standard economic theory suggests that manufacturers should increase drug prices in response to the gap closure, even had the closure not been partially funded through manufacturer rebates. In this Appendix, we calibrate a simple model of beneficiary demand to benchmark how much manufacturers should optimally increase drug prices due to the increase in beneficiary demand alone.

i. Beneficiary demand

Suppose we have a unit measure of non-LIS beneficiaries. In a given month t, beneficiary i consumes a single unit of prescription drugs with probability α_{it}. Denote $d_{it} = 1$ if beneficiary i consumes prescription drugs in month t. Probability of consumption is endogenous and depends on: (i) the price of the prescription drugs p and (ii) how much the beneficiary has consumed in previous months, which determines their contemporaneous cost-sharing $c_{it}\left(\cdot, \sum_{t'=1}^{t-1} p d_{it'}\right)$.

Expected annual revenue for manufacturers from non-LIS beneficiaries is given by:

$$E\left[\pi_L\right] = \sum_{t=1}^{12} E_i\left[p d_{it}\right]$$

where for simplicity, we assume that drug manufacturers have no marginal cost of production.[53] Expected revenue in month 1 is given by:

$$E_i\left[p d_{i1}\right] = p\alpha_{i1}\left(c_{i1}\left(p, 0\right)\right)$$

and the derivative of expected revenue in month 1 with respect to price is given by:

$$\frac{\partial}{\partial p} E_i\left[p d_{i1}\right] = \alpha_{i1}\left(c_{i1}\left(p, 0\right)\right) + p\frac{\partial \alpha_{i1}\left(c_{i1}\left(p, 0\right)\right)}{\partial c_{i1}\left(p, 0\right)} \frac{\partial c_{i1}\left(p, 0\right)}{\partial p}$$

We calibrate the probability of consumption α_{it} to match empirical probabilities in the Medicare Part D data when price is set to $p = 1$. We set the cost-sharing function c_{it} to the standard benefit plan in 2010. We calibrate the out-of-pocket price elasticity of consumption to $\frac{\partial \alpha_{it}}{\partial c_{it}} = -0.32$, to match the average price elasticity estimated in Einav et al. (2018) for the 160 most common branded drugs. Expected profit in month 2 is given by:

$$E_i\left[p d_{i2}\right] = \alpha_{i1}\left[p\alpha_{i2}\left(c_{i2}\left(p, p\right)\right)\right] + \left(1 - \alpha_{i1}\right)\left[p\alpha_{i2}\left(c_{i2}\left(p, 0\right)\right)\right]$$

Therefore, there is an additional indirect effect of price on the probability of consumption in

[53] The marginal cost of production for a branded drug is typically trivial relative to its sale price.

month 2 due to changes in the beneficiary's contemporaneous cost-sharing via direct effects of price on the probability of consumption in month 1. The dynamic nature of beneficiary consumption means that while an analytical solution to the derivative of expected revenue with respect to price $\frac{\partial}{\partial p}E[\pi_L]$ exists, in practice, it is unwieldy. Instead, we will numerically solve for the derivative $\frac{\partial}{\partial p}E[\pi_L]$ via simulation.

ii. Manufacturer response

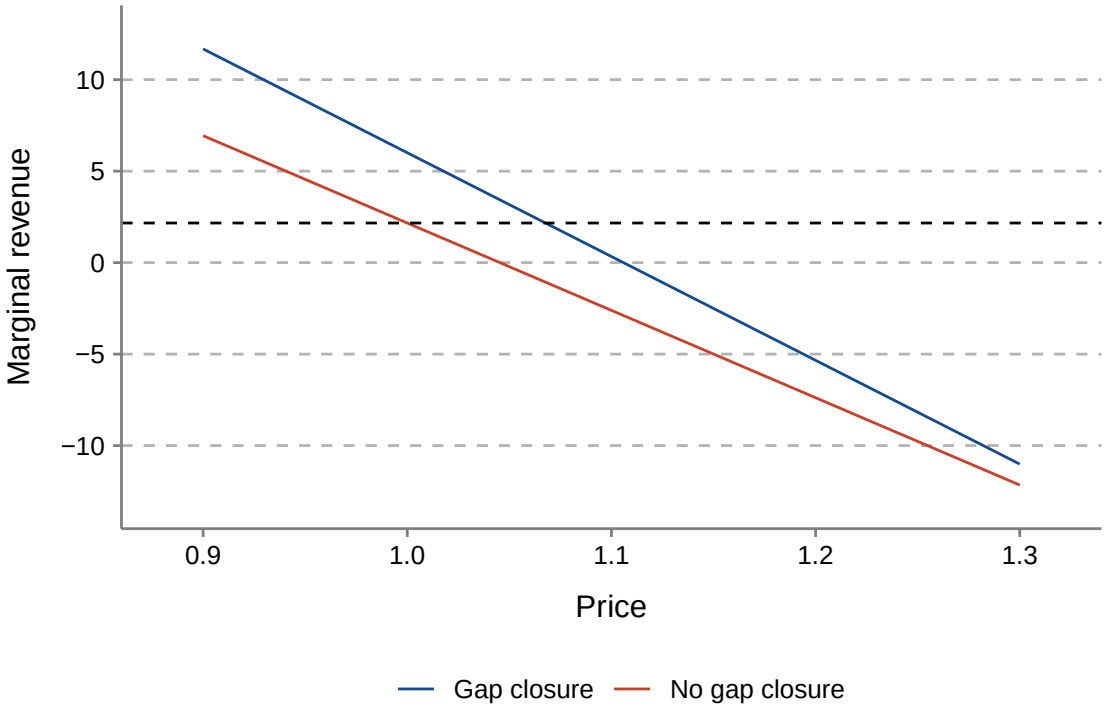
We assume that firms are profit-maximizing, meaning manufacturers set the price of prescription drugs such that marginal revenue equates some constant marginal shadow cost of increasing price:

$$\frac{\partial}{\partial p}E[\pi_L] = \lambda$$

Here, the marginal shadow cost of increasing price captures, for example, an increase in manufacturer rebates to insurers due to an increase in the price of prescription drugs. We can therefore use the firm's first order condition to infer the marginal shadow cost of increasing price. Since we calibrate the probability of consumption α_{it} to match empirical probabilities in the Medicare Part D data when price is set to $p = 1$, this price can be interpreted as the status quo price set by manufacturers. Therefore, the marginal shadow cost of increasing price is equal to the marginal revenue when prices are set to $p = 1$.

This allows us to calculate the profit-maximizing price for manufacturers given a change in the cost-sharing function $c_{it}(\cdot, \cdot)$. In particular, we calculate the profit-maximizing price from a change in the cost-sharing function due to the closure of the coverage gap. Figure A5 presents marginal revenue for manufacturers with and without the closure of the coverage gap. We find that manufacturers should optimally increase drug prices by 6% due to increase in beneficiary demand alone from the gap closure, warranting the need to analyze strategic responses by manufacturers.

Appendix Figure A5: Marginal revenue for manufacturers with and without gap closure



Note: Figure shows the simulated marginal revenue for manufacturers with and without the closure of the coverage gap. A price of $p = 1$ can be interpreted as the status quo price set by manufacturers.

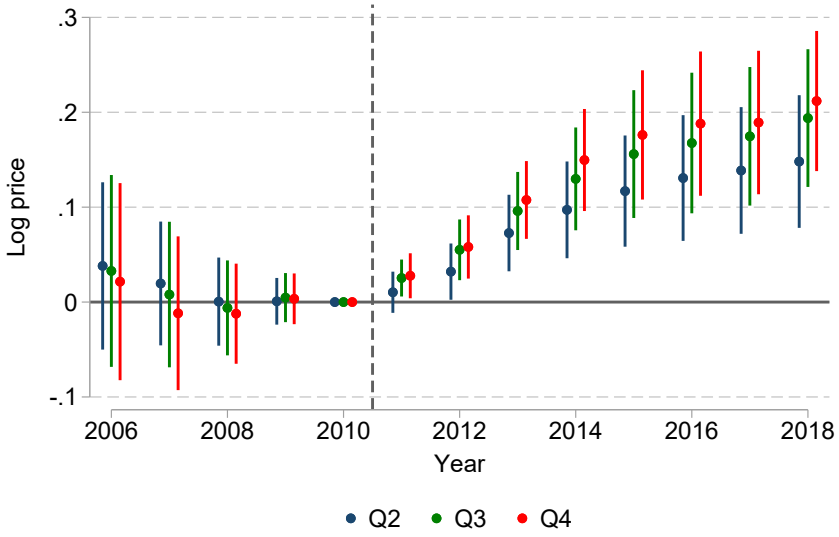
E: Event study with exposure quartiles

We augment the event study model with exposure indicator by separate indicator variables for drug-markets in the second, third, or fourth quartile of the *gap share* distribution. By splitting the *gap share* into quartiles, we allow the effect on retail prices to be non-linear in exposure. We estimate this specification separately for drugs with and without generic alternative.

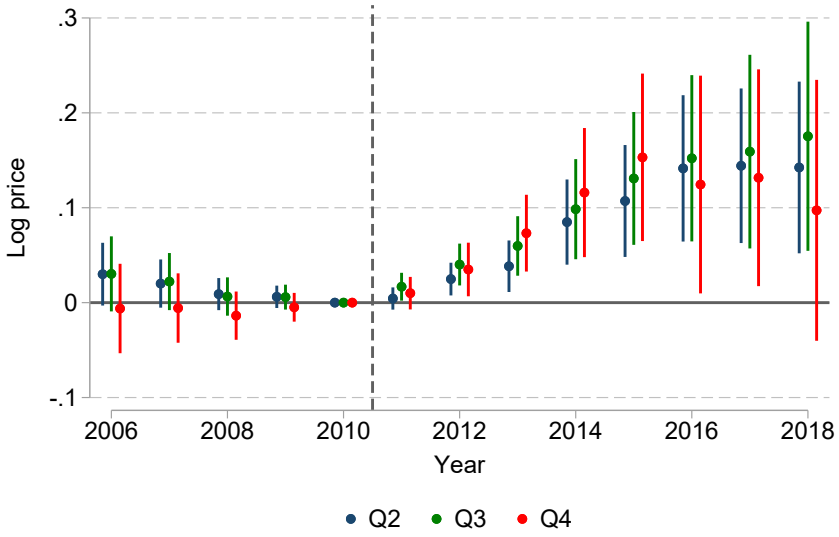
Figure A6 illustrates the results. We find a clear trend for drugs without generic competition: Consistently, the effect on prices is increasing across exposure quartiles, suggesting that manufacturers raised prices more if they were more reliant on revenue from non-LIS beneficiaries in the gap. For 2018, prices are 16% higher for drugs in the second quartile, relative to drugs in the first quartile, 21% higher for drugs in the third quartile, and 24% higher for drugs in the fourth quartile. While this trend holds qualitatively, point estimates are not statistically different across quartiles in most post-policy years. Overall, the results suggest that the effect on retail prices is concave in exposure: On average, drugs in the second quartile made 6.6% of their variable revenue from non-LIS in the gap, compared to 16.2% in the fourth quartile. For drugs with generic alternative, we detect the same trend in early post-policy years. Starting 2016, the differences across quartiles dissipate, presumably reflecting more stringent competition.

Appendix Figure A6: Effect of policy exposure on log price, exposure quartiles

(A) Without generic



(B) With generic



Note: Figure illustrates estimation results for our event study specification with separate indicator variables for the second, third, and fourth quartile of the *gap share* distribution. Our analysis sample are brand-name drugs sold in Part D in 2010. Our drug-market specific exposure measure is defined in Equation (2). In this specification, we compare drug-markets below the first quartile of the spending-weighted *gap share* distribution to drug-markets in the second, third, or fourth quartile. The event study includes drug-market, market-year, and patent expiration year-year specific fixed effects. We implement the event study separately for drugs with and without a generic alternative. We weight each observation by its drug-market revenue in 2010. Results show the point estimates and 95% confidence intervals. Standard errors are clustered at the drug level.

F: Measuring policy exposure including commercial spending

Our research design exploits variation in the exposure to the closing of the coverage gap. In this Appendix, we replicate our event study analysis using a variation of our exposure measure that additionally includes spending from beneficiaries with commercial insurance. Specifically, we measure policy exposure as drug j's revenue from non-LIS beneficiaries in the gap relative to the *variable* revenue in market m in 2010,

$$gap\ share_{jm|2010} = \frac{non\text{-}LIS\ gap_{jm|2010}}{(Part\ D_{jm|2010} - Part\ D\ government_{jm|2010}) + commercial_{jm|2010}} \tag{6}$$

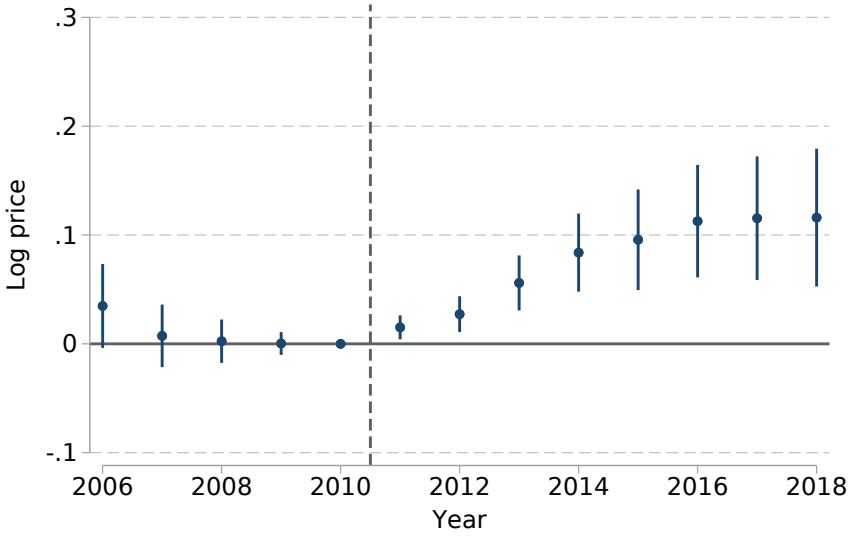
The numerator of the *gap share* is spending from claims by non-LIS beneficiaries in the gap in 2010. The denominator is market-wide total spending in 2010 (i.e., Part D spending and commercial spending) minus Part D government-financed spending, comprising LIS cost-sharing subsidies and non-LIS reinsurance in the catastrophic phase.

To calculate commercial spending, we use 2010 prescription claims from beneficiaries with commercial insurance in the Merative MarketScan® Research Databases (PHS 2025). The Merative MarketScan® Research Databases provides deidentified, longitudinal, patient-level claims data from 2007 to 2022 for over 250 million beneficiaries enrolled in commercial plans across the U.S. To ensure comparability across data sources, we use sampling weights derived from the American Community Survey to ensure that commercial spending is nationally representative (Hirsch 2024). Our sample of Part D beneficiaries is derived from a 20% random sample of the Medicare population, and we only include beneficiaries enrolled in a Part D standalone prescription drug plan (PDPs). For comparability, we multiply Part D spending by 5, and for each market, we multiply by the reciprocal of the Part D market share held by PDPs.

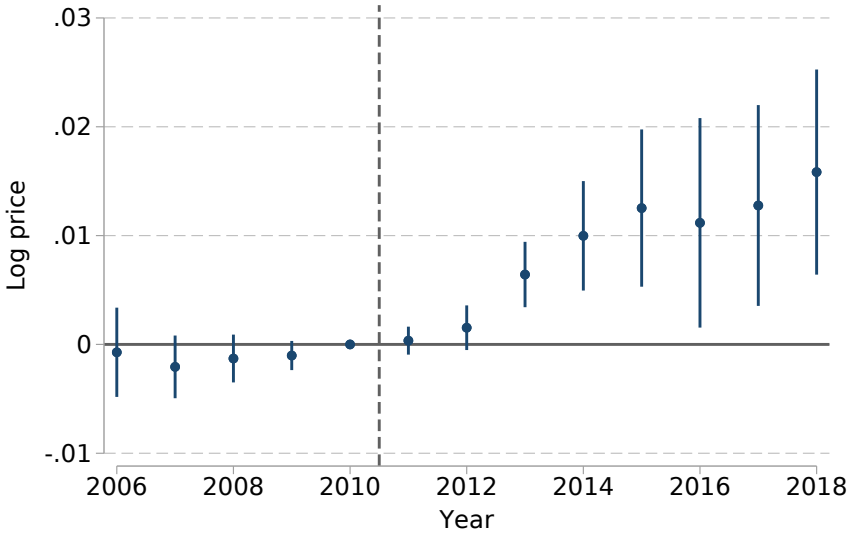
Figure A7 presents the regression results for event study specification (3) using our exposure measure that includes commercial spending. Regression results are less precise, but qualitatively similar. Our results are therefore robust to incorporating commercial spending into our exposure measure. However, we use the measure defined in Equation (2) as our preferred measure of policy exposure given that commercial and Part D beneficiaries are institutionally segmented. For example, manufacturers can directly provide price concessions to commercial beneficiaries through copay coupons, whereas the Anti-Kickback Statute prohibits Part D beneficiaries from using such coupons.

Appendix Figure A7: Effect of policy exposure on log price, baseline specifications

(A) Exposure indicator



(B) Linear exposure effect



Note: This figure illustrates the estimation results for our baseline event study specifications (3), with the exposure indicator (Panel (A)) and the linear exposure effect (Panel (B)). Our analysis sample are brand-name drugs sold in Part D markets in 2010. The exposure measure is defined in Equation (6). In Panel (A), we compare drug-markets above versus below the first quartile of the spending-weighted *gap share* distribution. In Panel (B), we impose a linear effect of policy exposure on log prices. Both event studies include drug×market, market×year, and patent expiration year×year fixed effects. We weight each observation by its drug-market revenue in 2010. Results show the point estimates $\hat{\beta}_t$ and 95% confidence intervals. Standard errors are clustered at the drug level.

G: Distributional implications

In Section IV and Section V, we document two effects of the policy change: Non-LIS beneficiaries are less likely to forgo prescription drugs upon reaching the coverage gap, and retail prices increased in response to the discount requirement and demand increase that manufacturers faced. To illustrate the qualitative implications of the endogenous price response, we examine the distributional incidence of the closing of the coverage gap across beneficiaries and the other payers in the market. We provide two pieces of model-free evidence: We first illustrate how drug spending is reallocated mechanically by the redesign of the coverage gap, and then isolate the effect of the price increase on the relative incidence across payers.

In our back-of-the-envelope calculations, we let beneficiaries progress through the standard plan design with the pre- and post-ACA cost-sharing in the coverage gap. Using the government-defined cost-sharing function, we can immediately read off how each marginal dollar of drug spending is split between payers—that is, beneficiaries, government, insurer, and manufacturer. We calculate the change in payer-specific spending using both prices and quantities before the policy change in 2010 (in the style of a Laspeyres price index), and prices and quantities after the policy change in 2015 (in the style of a Paasche price index). That is, for each payer k and beneficiary i, we compute the following two indices,

$$\Delta \mathrm{L}_k^{2010}(i) = C_{k,2015}^{2010}\left(\sum_j p_{jm}^{2010} \times (1+\beta_{jm}) \times Q_{ij}^{2010}\right) - C_{k,2010}^{2010}\left(\sum_j p_{jm}^{2010} \times Q_{ij}^{2010}\right) \tag{7}$$

and

$$\Delta \mathrm{P}_k^{2015}(i) = C_{k,2015}^{2015}\left(\sum_j p_{jm}^{2015} \times Q_{ij}^{2015}\right) - C_{k,2010}^{2015}\left(\sum_j p_{jm}^{2015} \times (1+\beta_{jm})^{-1} \times Q_{ij}^{2015}\right) \tag{8}$$

Here, $C_{k,g}^t(\cdot)$ is the cost-sharing function for payer k implied by the standard plan design in year t with gap cost-sharing from year g, p_{jm}^t is the retail price of drug j in market m in year t, and Q_{ij}^t is the quantity of drug j consumed by beneficiary i in year t. The term β_{jm} captures the endogenous price response by manufacturers.

For the Laspeyres-style index, $\Delta \mathrm{L}_k^{2010}$, we focus on beneficiaries in 2010 and hold their prescription drug consumption fixed throughout. The second term of Equation (7) measures expenditure by payer k on beneficiary i at 2010 prices and the 2010 cost-sharing in the coverage gap. This corresponds to observed spending if the beneficiary was indeed enrolled in a plan with the standard benefit design. The first term of Equation (7) measures the counterfactual expenditure at 2010 prices, scaled by the endogenous price response, and the 2015 gap cost-sharing. To get the mechanical effect of the policy change, absent a price response, we set β_{jm} equal to zero. For the full effect, we set β_{jm} equal to the predicted effect based on the event study model with linear exposure effect that splits our sample of brand-name drugs by generic availability.[54] The Paasche-style index, $\Delta \mathrm{P}_k^{2015}$, is based on

[54] See Columns (6) and (7) in Table A3 for the estimation results. In the counterfactual, we only change the cost-sharing in the coverage gap and hold the spending limits that mark the coverage phase thresholds fixed.

beneficiaries in 2015. Here, we compare payer-specific spending at 2015 prices and the 2015 gap cost-sharing to counterfactual spending under the 2010 gap design, with and without prices adjusted for the endogenous effect.[55]

We further adjust manufacturer spending to account for reallocation via post-sale rebates, uniformly applying the average rebate rate in each year. For instance, the average rebate rate for brand-name drugs was 15% in 2010 (Boards of Trustees for Medicare 2014). Thus, for the Laspeyres-style index, we apportion 15% of the additional cost per claim for brand-name drugs—arising from the endogenous price response—to post-sale rebates.[56] This amount is then reallocated away from manufacturers. For clarity, we treat changes in post-sale rebates as a separate account, even though rebates are nominally transferred to insurers.[57] See Online Appendix B for a detailed discussion about post-sale rebates in Medicare Part D.

Our distributional analysis is a first-order approximation as we do not account for the beneficiary's spending response to cost-sharing and price changes. Thus, the Laspeyres-style index will overestimate the reduction in beneficiary out-of-pocket spending because it does not capture the demand increase due to the closing of the coverage gap. In return, the Paasche-style index will underestimate the reduction in out-of-pocket spending because it does not capture the decrease in drug consumption as we counterfactually return to the 2010 gap cost-sharing design. Therefore, the indices provide an upper and lower bound on the incidence of the policy change. Due to these caveats, our exercise is intended to demonstrate the qualitative significance of the endogenous price response rather than provide an exact quantification.

Figure A8 illustrates the results of the back-of-the-envelope calculations. Panel (A) shows the mechanical effect of the policy change, that is, the per capita reallocation of spending due to the benefit redesign. Panel (B) shows the combined effect of gap closure and endogenous price response. Overall, we find that the insurance expansion intended a per capita transfer of $100 to beneficiaries that is largely financed by manufacturers. With prices fixed, insurers bear some cost of the expansion due to additional cost-sharing in the gap, but government financing of drug spending remains unchanged. Accounting for the price response dramatically shifts the incidence: beneficiaries only receive a per capita transfer of $55. Manufacturers benefit from the policy change by raising prices and the additional spending is primarily financed by the government. Costs borne by insurers from higher prices are compensated by increases in post-sale rebates.

Notably, the majority of beneficiaries actually experience higher out-of-pocket costs. While the average beneficiary receives a $55 transfer, the median beneficiary incurs a $7

[55] We chose the 2015 gap design as our counterfactual because, as in the final gap design in 2020 onward, insurance plans had to cover 5% of branded drug spending in the gap. In addition, the exposure effect stabilized in 2015. We set β_{jm} to zero for generic drugs and brand-name drugs that are not included in our analysis of the manufacturer response.

[56] By applying a uniform rebate rate, we assume that drug-specific changes in rebate rates are uncorrelated with policy exposure or the endogenous price response. The direction of rebate changes is ex-ante ambiguous as manufacturers are required to provide the gap discount in parallel to other direct and indirect remuneration. Based on Boards of Trustees for Medicare (2014, 2020), we estimate an average rebate rate for brand-name drugs of 15% in 2010 and of 30% in 2015.

[57] CMS accounts for post-sale rebates when determining direct subsidies to insurers. Insurers may also return post-sale rebates to beneficiaries in the form of lower premiums, although we do not observe significant changes in inflation-adjusted plan premiums from 2010 to 2018.

cost. To highlight the heterogeneous impact of the insurance expansion, Figure A9 shows a histogram of the distributional incidence across beneficiaries when allowing for an endogenous price response. The majority of beneficiaries—i.e., non-LIS beneficiaries who do not spend in the gap and LIS beneficiaries—mechanically cannot benefit from the gap closure. However, higher retail prices increase their out-of-pocket costs due to cost-sharing in all coverage phases.

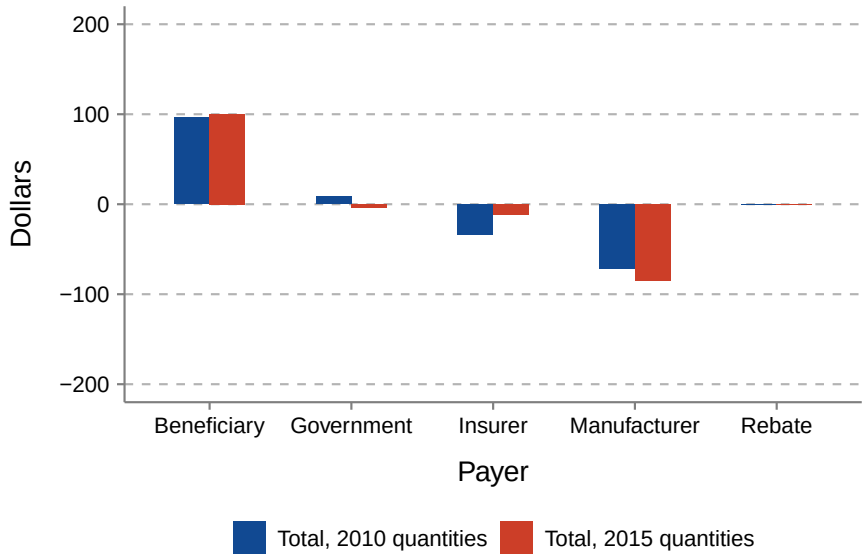
To further illustrate the mechanics behind our aggregate results, Figure A10 decomposes the distributional incidence by beneficiary group. This exercise demonstrates the spillover effects of the low-income subsidy, despite the policy change not directly impacting this consumer segment. We find that, by raising prices, manufacturers can cut their losses from non-LIS beneficiaries who receive the coverage gap discount. Furthermore, manufacturers benefit from LIS beneficiaries, who consume at higher prices at the expense of the government. Via this channel, drug manufacturers can shift the incidence of discount payments onto the government. Insurers are largely unaffected by the policy change and shielded from the price increase due to post-sale rebates.[58]

Overall, we find that the endogenous price response by manufacturers is quantitatively important for the incidence of the insurance expansion. We caveat that our results on the manufacturer incidence assume that rebate rates are exogenous, and we hold the average rebate rate in a given year fixed. Although we cannot speak to the effects of the gap closure on net-of-rebate prices, beneficiaries face retail prices when purchasing prescription drugs. Therefore, while we do not observe post-sale rebates, we still quantify the effect of the gap closure on beneficiary out-of-pocket costs.

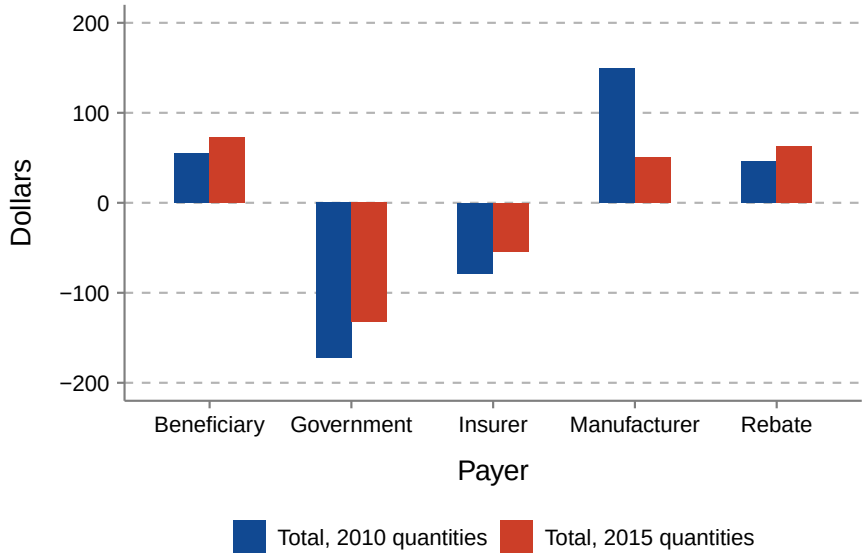
[58] While any losses or gains to insurers could be passed on to beneficiaries via changes in insurance premiums, we do not find significant changes in inflation-adjusted premiums in the years after the gap closure began.

Appendix Figure A8: Distributional incidence of coverage gap closure

(A) Without endogenous price response

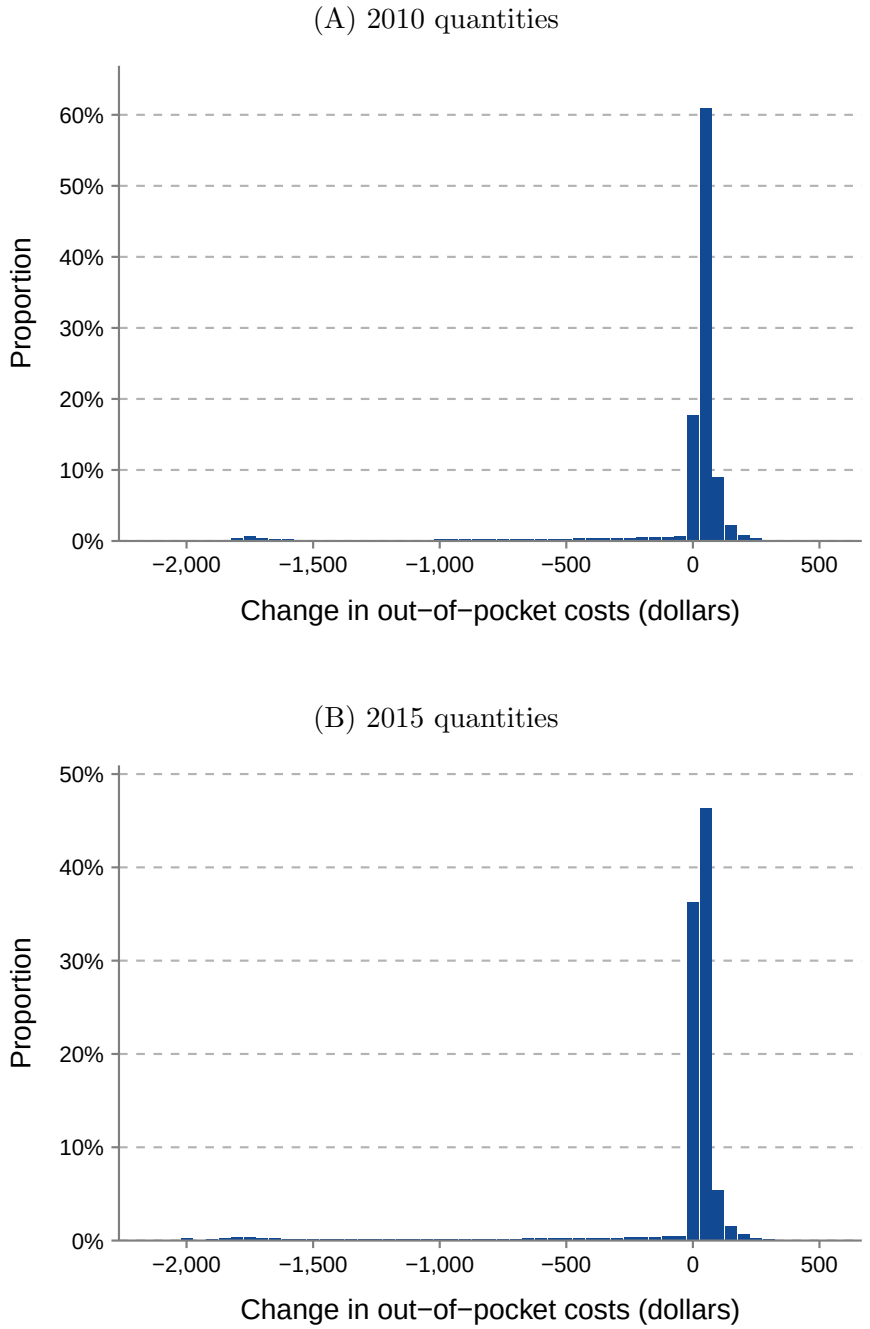


(B) With endogenous price response



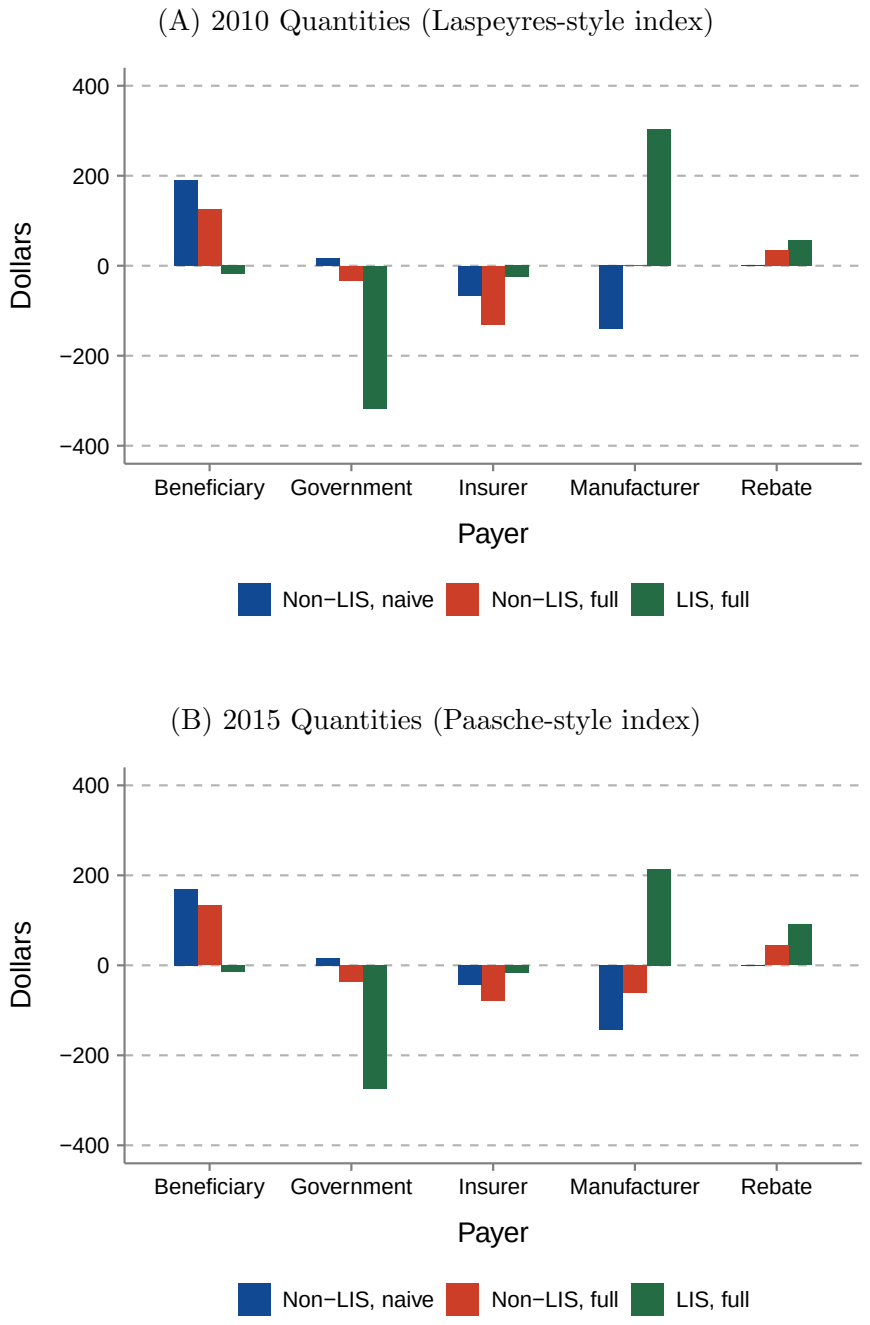
Note: Figure shows the distributional incidence of the closure of the coverage gap by payer (beneficiary, government, insurer, and manufacturer) based on 2010 quantities (Laspeyres-style index) and based on 2015 quantities (Paasche-style index). Panel (A) shows the reallocation of spending across payers arising from the benefit redesign, holding prices fixed at their 2010 or 2015 level. Panel (B) shows the reallocation of spending across payers arising from the benefit redesign and the endogenous price response by manufacturers. To calculate the endogenous price response, we use the predicted effect on prices from the event study model with linear exposure effect that splits our sample of brand-name drugs by generic availability. For drugs not in our analysis sample, we hold prices fixed at their respective level. The allocation of spending for 'manufacturer" accounts for the average post-sale rebate level for brand-name drugs in 2010 (15%) and in 2015 (30%). Post-sale rebates are separately presented, though nominally would be allocated to insurers.

Appendix Figure A9: Distributional incidence of coverage gap closure with endogenous price response, by beneficiary



Note: Figure shows the distributional incidence of the closure of the coverage gap on out-of-pocket costs of beneficiary, based on 2010 quantities (Laspeyres-style index) and based on 2015 quantities (Paasche-style index). To calculate the endogenous price response, we use the predicted effect on prices from the event study model with linear exposure effect that splits our sample of brand-name drugs by generic availability. For drugs not in our analysis sample, we hold prices fixed at their respective level.

Appendix Figure A10: Distributional incidence of coverage gap closure, by beneficiary group



Note: Figure illustrates the mechanics behind our back-of-the-envelope calculations of the distributional incidence of the closure of the coverage gap based on 2010 quantities (Laspeyres-style index, Panel (A)) and 2015 quantities (Paasche-style index, Panel (B)). Figure shows the reallocation of spending across payers (beneficiary, government, insurer, and manufacturer) for the following cases: "Non-LIS, naive" shows the reallocation of spending by non-LIS beneficiaries that arises mechanically by the benefit redesign, holding prices fixed at their 2010 or 2015 levels. Notably, there is no mechanical reallocation of spending for LIS beneficiaries because they do not experience the coverage gap. "Non-LIS, full" shows the reallocation of spending by non-LIS beneficiaries that arises by the benefit redesign and the endogenous price response. "LIS, full" shows the reallocation of spending by LIS beneficiaries that arises from the endogenous price response. The allocation of spending for 'manufacturer" accounts for the average post-sale rebate level for brand-name drugs in 2010 (15%) and in 2015 (30%). Post-sale rebates are separately presented, though nominally would be allocated to insurers.

H: Post-sale rebates for brand-name drugs in Medicare Part D

In this section, we argue that our results are robust to the existence of post-sale rebates for brand-name drugs. These rebates are price concessions that manufacturers pay insurers for preferential formulary placement. Prior studies have documented that such rebates have increased considerably over the past decade. We show that these findings are not directly applicable to our setting and that the evidence on increases in rebates in Medicare Part D is less conclusive. In addition, we demonstrate that our empirical findings hold for brand-name drugs in protected drug classes where manufacturers face limited incentives to provide post-sale rebates.

Limitations. In Section V, we document that the discount requirement and demand increase following the gap close led to an increase in retail prices. One concern is that manufacturers concurrently increased rebate rates, meaning that net-of-rebate prices may have actually remained constant. It is theoretically unclear whether manufacturers would increase or decrease the rebate rate in response to the gap discount. On the one hand, manufacturers have to provide an additional discount in the coverage gap and may prefer to reduce other price concessions.[59] On the other hand, insurers may demand higher rebates as they have to cover at least a small portion of gap spending.

We cannot empirically test whether drug-level changes in rebate rates are correlated with policy exposure due to data limitations.[60] While we cannot account for drug-level changes in rebates, the effect of the gap closure on retail prices is nonetheless important: Beneficiaries who are not eligible for LIS are exposed to this price increase via cost-sharing. Therefore, retail prices are enough to quantify the effects of the gap closure on out-of-pocket costs for beneficiaries. Higher retail prices also push beneficiaries more quickly to the catastrophic coverage phase, where the federal government pays for the majority of drug spending at retail price.

Evidence from SEC filings. Several studies have analyzed estimates of net-of-rebate prices derived from SEC filings of publicly traded pharmaceutical companies (Hernandez et al. 2020; Kakani, Chernew, and Chandra 2020; Sood et al. 2020).[61] These studies consistently find that economy-wide rebate rates increased considerably over the past decade. However, these results are not directly applicable to our setting for two reasons. First, these studies average

[59] In a survey by the U.S. Government Accountability Office, pharmacy benefit managers "observed that some manufacturers decreased the amount of rebates for the brand-name drugs they offered, which they believe occurred as a result of the Discount Program." Pharmacy benefit managers also "believed the Discount Program may have been a contributing factor in the rising prices of some brand-name drugs by some manufacturers" (GAO 2012).

[60] By including market-year fixed effects, our event study flexibly controls for the average change in rebate rates in a market over time. By including patent expiration year × year fixed effects, we also control for changes in rebate rates over the drug life cycle (e.g., one could imagine that manufacturers increase rebates as a drug approaches patent expiration).

[61] These studies rely on data from SSR Health, LLC. To estimate net prices, SSR Health aggregates data on net revenue from SEC filings, data on list prices and unit sales from Symphony Health, and dosing information from FDA labels.

across all U.S. payers and capture all types of price concessions provided to insurers and consumers. In particular, they include mandatory Medicaid rebates, which are significantly higher than Medicare rebates,[62] copay coupons (or "copay cards") and 340B discounts, which are both not available to Part D beneficiaries due to the Anti-Kickback Statute.[63] Second, and most notably, net-of-rebate prices derived from SEC filings after 2010 treat manufacturer discounts from the *Coverage Gap Discount Program* as a rebate.[64] Consequently, changes in rebate amounts derived from SEC filings will be mechanically correlated with policy exposure, rendering this data uninformative for our study.

Evidence from government reports. Focusing exclusively on Medicare Part D, the Boards of Trustees for Medicare (2014; 2020) report annual rebate payments as a percentage of total drug costs. Figure A11 illustrates the trend in the spending-weighted average rebate rate. Notably, the rate remains fairly stable in the first years after the gap closure, and the subsequent increase coincides with the launch of several high-cost Hepatitis C drugs in 2014-2017, which carry high rebates (Boards of Trustees for Medicare 2019). Thus, the trend is likely confounded by compositional changes over time and, therefore, not directly applicable to our analysis as we only consider drugs that were already sold in Part D in 2010.

Closest to our setup, a report by the Office of the Inspector General (2019) studies rebate trends in Part D for 1,510 brand-name drugs that were sold in all years between 2011-2015. The report finds that nominal rebate payments are highly concentrated, with about 10% of drugs accounting for 90% of the total rebate amount. In addition, 58% of reviewed drugs experienced an increase in the per-unit rebate amount over time, while 42% experienced a decrease. While almost all drugs saw an increase in the retail price, the rebated amount increased for only 56% of drugs. Overall, the rebate rate decreased for over half of reviewed drugs: the median rebate rate was 1.6% in 2011 and 0.3% in 2015. These numbers suggest that Part D rebate rates of incumbent drugs were fairly stable over time. In conclusion, there is mixed evidence on the level and trend of rebate rates in Medicare Part D.

Evidence from drugs in protected drug classes. As a robustness check, we estimate our baseline event study specification (3) focusing on branded drugs in protected drug classes. Medicare Part D has six protected classes of drugs that all plans must include in their formulary. Manufacturers have little incentive to offer post-sale rebates to insurers if coverage of a drug is required. For example, among the top 15 therapeutic classes of drugs covered under Part D by gross spending, average rebate rates in 2021 were between 0% and 9% for protected classes versus an average of 38% for other classes (MedPAC 2023). Figure A12 illustrates the regression results for branded drugs in protected classes only. In both

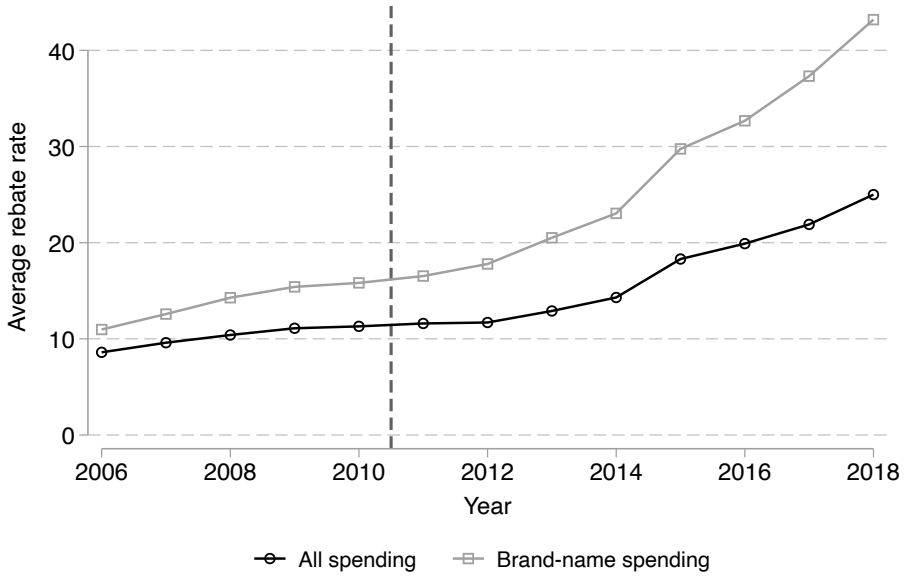
[62] Only Sood et al. (2020) single out Medicaid rebates and find that discounts across all other U.S. payers increased from 23% to 51% between 2007-2018.

[63] Over this period, the availability of copay coupons for brand-name drugs increased considerably and the share of branded drug spending with a coupon in the private insurance market increased from 26% in 2007 to 93% in 2017 (Dafny, Ho, and Kong 2022).

[64] For example, net-of-rebate revenue in the 2015 10-K filing for the Bristol-Myers Squibb Company include adjustments for the "50% point of service discount to the Centers for Medicare & Medicaid Services when the Medicare Part D beneficiaries are in the coverage gap." Similarly, net-of-rebate revenue in the 2015 10-K filing for Pfizer include adjustments for "discounts on branded prescription drug sales to Medicare Part D participants in the Medicare coverage gap."

specifications, we find a positive and statistically significant effect of policy exposure on retail prices in the years following the gap closure. Results are quantitatively similar to our main results in Figure 6, suggesting that our main results reflect an actual increase in drug prices.

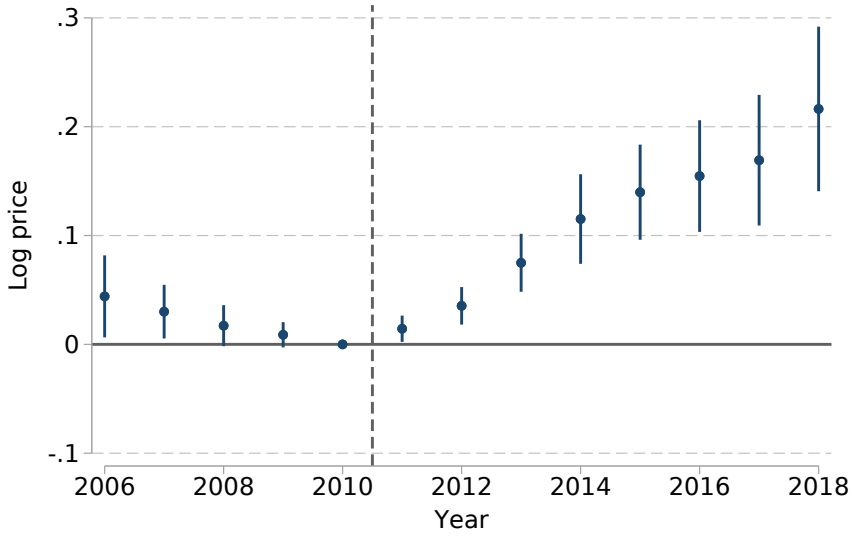
Appendix Figure A11: Average Medicare Part D rebate rate



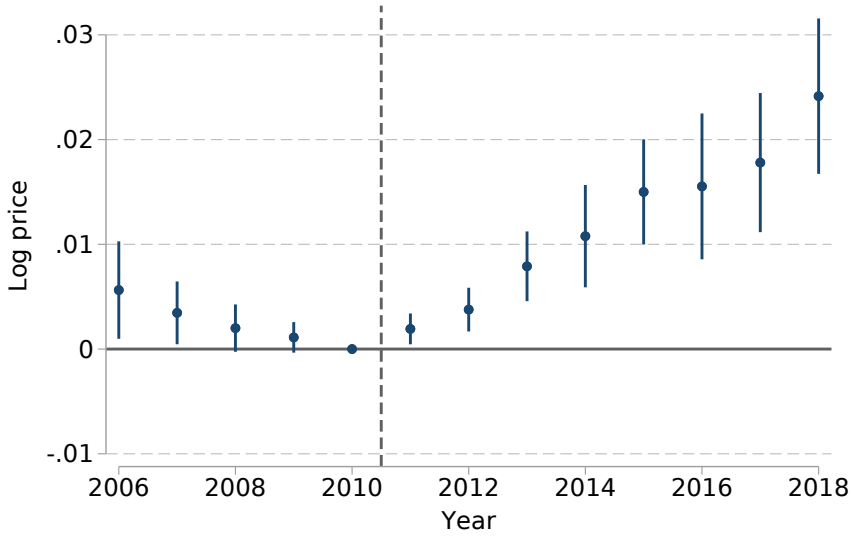
Note: Figure shows the average rebate rate in Medicare Part D, as reported by The Boards of Trustees for Medicare (2014; 2020). Rebate rate is total direct and indirect remuneration negotiated by Part D plans with drug manufacturers and pharmacies divided by total drug cost. The black line (with circles) illustrates the spending-weighted average rate. The gray line (with squares) is a conservative upper bound for the spending-weighted average rebate rate for brand-name drugs, accounting for the aggregate decrease in spending on brand-name drugs (relative to generic drugs) and assuming that generic drugs have zero remunerations.

Appendix Figure A12: Effect of policy exposure on log price for drugs in protected classes, baseline specifications

(A) Exposure indicator



(B) Linear exposure effect



Note: This figure illustrates the estimation results for our baseline event study specifications (3), with the exposure indicator (Panel (A)) and the linear exposure effect (Panel (B)). Our analysis sample are brand-name drugs in protected classes sold in Part D markets in 2010. The exposure measure is defined in Equation (6). In Panel (A), we compare drug-markets above versus below the first quartile of the spending-weighted *gap share* distribution. In Panel (B), we impose a linear effect of policy exposure on log prices. Both event studies include drug×market, market×year, and patent expiration year×year fixed effects. We weight each observation by its drug-market revenue in 2010. Results show the point estimates $\hat{\beta}_t$ and 95% confidence intervals. Standard errors are clustered at the drug level.

I: Further provisions of the ACA related to the pharmaceutical market

This Appendix summarizes further provisions that were implemented as part of the Affordable Care Act and involved the pharmaceutical market. The timeline is based on the Board on Health Care Services (2014), Aitken et al. (2016) and Conti, Dusetzina, and Sachs (2020). We do not believe any of these provisions would differentially impact drugs with high exposure to the *Coverage Gap Discount Program*.

1. Starting January 2010, the mandatory minimum rebate that manufacturers have to provide for brand-name drugs sold under *Medicaid* increased from 15.1% to 23.1%. In addition, manufacturers have to pay an additional rebate if drug prices increase faster than inflation. The latter provision has been the main reason for the rise of Medicaid rebates over time (Office of Inspection General 2019a). Notably, dual-eligible beneficiaries, who receive both Medicare and Medicaid, receive drug coverage primarily through Medicare and are included in our empirical analysis.

2. Starting January 2011, drug companies with annual sales to government programs exceeding $5 million have to collectively finance the *Branded Prescription Drug Fee* of $2.5-4.1 billion annually, which funds the *Medicare Part B* Trust Fund. The fee per drug company is proportional to annual sales.

3. Starting October 2013, the *ACA Marketplaces* opened for enrollment.

4. Starting January 2014, *ACA expansion states* increased Medicaid eligibility criteria for all low-income adults.