Online Appendix

Profiting from Most-Favored Customer Procurement Rules: Evidence from Medicaid

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A SSR HEALTH DATA AND SAMPLE SELECTION

A.1 Net Sales Data

The net sales data collected by SSR Health (SSR Health, 2019) come directly from company financial filings (10-Q and 10-K). In recent years, drug manufacturers have started reporting net sales by drug and country/region, at least for their top-selling drugs. The reports usually cover patent-protected drugs only. Once branded drugs lose exclusivity, their annual sales typically drop ninety percent or more. SSR collects these figures every quarter, resulting in a dataset that covers on-patent branded drugs sold by publicly traded companies.[1]

This source provides a very accurate picture of the amount of revenue received by manufacturers. However, when it comes to measuring rebates there are three issues that need to be considered. First, there is a discrepancy between the time when net sales are recorded, and the time when volume and invoice sales are record. This discrepancy creates a source of noise when computing prices and discounts in a given year. Net sales are typically recorded when the manufacturer sells to a wholesaler. On the other hand, the typical sources for volume and invoice sales data are based on when prescriptions are actually filled.[2] Therefore, if a drug manufacturer ships off a large amount in December of a given year, this will lead to an increase in recorded net sales in that year, even though most of the corresponding volume and invoice sales will be recorded in the next year.[3] The timing of rebates and discounts also matters. While rebates and discounts are resolved on a quarterly basis (this is the case of the Medicaid rebate, for example), it is possible that some of these payments may occur less regularly. This can show up in the data as additional noise.

Second, net sales take into account firm payments that should not be characterized as discounts. The main example is copay assistance programs, which became more prominent starting around 2005.[4] Average rebates calculated from the SSR Health data may overestimate the rebates slightly as a result. This may also impact estimated changes in rebates if spending on copay assistance changes from year to year. Beyond their direct impact on rebate measures, these programs can also increase the bargaining power of manufacturers, by limiting the ability of PBMs to control demand.

The third and final issue is that invoice and net sales are reported at the drug level. These numbers are potentially aggregated across many different forms, strengths, and drug package types. This should not create problems for our analysis, unless the composition of products within a drug changes in a systematic way that is correlated with MMS.

[1] Most pharmaceutical companies are publicly traded. The most prominent exclusion is Boehringer Ingelheim.

[2] This includes our source (Symphony Health), but also other sources, such as IQVIA.

[3] The noise issue is obviously much worse when using quarterly data, which is partly what motivated us to use yearly data in our regressions.

[4] Some firms also report this as SG&A (overhead).

A.2 Estimates of the Medicaid Rebate

Our analysis also relies on Medicaid rebates estimated by SSR Health. We briefly discuss their methodology. The Medicaid rebate is a function of initial Average Manufacturer Price (AMP), current AMP, and the best commercial market price.

SSR uses a methodology that deviates from the Medicaid rule in two ways. First, since AMP is proprietary information disclosed only to the government, SSR Health uses the Wholesale Acquisition Cost as a replacement. In their estimates of Medicaid rebate, SSR adjusts WAC downward by 3% to reflect an estimated difference between these two price points. We do not use this convention, preferring instead, for simplicity, to set WAC equal to AMP.[5] Second, SSR Health does not factor in best price into their Medicaid rebate calculations because data on best price is not publicly available.

In addition the process involves some imputation for drugs that were launched before 2007 (the first year of data they collect). For these drugs, SSR Health collects launch date and initial list price data going back to the 1990s. Launch date is available for all drugs. For drugs where information on initial launch price is not available, they impute pre-2007 growth in Wholesale Acquisition Cost (WAC) based on the average annual WAC growth rate across all drugs during the relevant time period.

A.3 Summary Statistics on the Samples Used in the Analysis

Finally, we discuss our sample selection in greater detail. We then present statistics on MMS stability and coverage for the different samples.

We choose to exclude certain drugs from our sample because of inaccuracies in reported volume and invoice sales. Symphony Health does not have good coverage of drugs administered in outpatient settings, as well as drugs sold through specialty pharmacies. Hence, for a number of drugs in our data, net sales regularly exceed invoice sales; a clear logical impossibility. The underreporting of invoice sales affects our estimates of Medicaid Market Share (MMS) because Medicaid spending data is more complete. Thus, many drugs with minimal exposure to the Medicaid market actually appear with very high MMS in our data. Our data sharing agreement prevents us from providing individual examples, but these drugs tend to be drugs administered in inpatient settings and targeted at an older population.

We apply two filters to account for this issue. The first filter (FHM) eliminates drugs that have excess net sales above invoice sales. As discussed above, timing issues can affect net sales and invoice sales. To be conservative, we apply the filter only if net sales are greater than gross sales over the entire period in which a drug is the SSR sample or if net sales are more than 50% greater than gross sales in any given year other than the launch year and year before loss-of-exclusivity. The main downside of this approach is that it uses data which is then used to generate some of

[5] We have repeated our entire analysis using both approaches and found no substantive differences between the two sets of results.

Table A1: The Impact of the MDRP Change on Private Market Outcomes

	MMS 2009						
MMS 2008	0.0121	0.954	0.0114	0.954	0.0110	0.0106	0.346
	(0.0125)	(0.0299)	(0.0122)	(0.0231)	(0.0121)	(0.0119)	(0.0780)
Sample	All	Core	Not Core	FHM	Not FHM	KCC	Not KCC
N	527	184	343	266	261	360	167
R^2	0.035	0.959	0.038	0.967	0.038	0.061	0.226

Notes: The smaller number of drugs relative to our core sample (197 drugs) is due to some drugs not having launched in 2008. Robust standard errors. $+p < 0.1$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$.

Table A2: Coverage of Different Samples (2009 Statistics)

Sample	Total Net Revenue ($bill)	Top 50	Top 100	Top 200	N
SSR Health	176.2	50	100	200	572
FHM Sample	153.0	45	89	162	286
KCC Sample	102.5	26	58	126	392
Core Sample	87.4	23	52	103	198

Notes: Top 50, Top 100, Top 200 refer to the number of drugs covered in the sample that are in the Top X drugs ranked by 2009 net sales. Revenue numbers are adjusted to year 2000 dollars. IMS Health estimates put total gross revenue for prescription drugs (including generics) at $300 billion in 2009 ($241 billion after adjusting for inflation).

the variables of interest. We believe this is unlikely to affect our results, because the first filter is based on the drug's entire lifecycle, while the second filter is equally likely to be triggered before and after the rule change.

The second filter (KCC) is based on the work in Kakani et al. (2020). We apply their approach to our sample, which covers an older set of drugs. Specifically, we filter out all injectables, vaccines, devices, and oncology drugs, in order to arrive at a sample that is primarily sold through retail pharmacies. In the main analysis we use the intersection of the FHM and KCC samples as the "core" sample.

We assess the performance of these samples by testing the consistency of the Medicaid Market Share across years, and by computing their coverage of top-selling drugs. The core sample and the FHM sample perform the best in terms of consistent MMS across years and coverage of top-selling drugs. To look for MMS consistency across years we regress 2009 MMS on 2008 MMS for each sample. Table A1 shows that the core sample and the FHM sample have coefficients that are close to and statistically indistinguishable from 1 and high R-squared, whereas the excluded sample exhibits very weak correlation across years. In addition, we also compute the coverage of top-selling drugs using 2009 data. Table A2 shows that the core sample covers about half of all drugs, while the FHM sample covers a majority of top-selling drugs.

B Proofs and Extensions to the Bargaining Model

B.1 Proof of Proposition 1

$$1 - d^{\mathrm{NB}} = \begin{cases} \frac{1}{\frac{1-b}{b} \times (-p_{\mathrm{list}}) \frac{\partial \log \Delta\Pi\left(p_{\mathrm{list}}\left(1-d^{\mathrm{NB}}\right)\right)}{\partial x}} & \text{if } d^{\mathrm{NB}} \leq r \\ \frac{1}{\frac{1-b}{b} \times (-p_{\mathrm{list}}) \frac{\partial \log \Delta\Pi\left(p_{\mathrm{list}}\left(1-d^{\mathrm{NB}}\right)\right)}{\partial x}} + (1-r) \times MMS & \text{if } d^{\mathrm{NB}} > r \end{cases} \tag{1}$$

Proof. Using the FOC from Equation 3, let d^{NB}be an implicit function of r. with respect to r. The first arm trivially yields $\frac{\partial d^{\mathrm{NB}}}{\partial r} = 0$. In the second arm:

$$-\frac{\partial d^{\mathrm{NB}}}{\partial r} = \frac{\frac{1-b}{b} \times p_{\mathrm{list}} \times \frac{\partial^2 \log \Delta\Pi\left(p_{\mathrm{list}}\left(1-d^{\mathrm{NB}}\right)\right)}{\partial x^2}}{\left(\frac{1-b}{b} \times (-p_{\mathrm{list}}) \frac{\partial \log \Delta\Pi(p_{\mathrm{list}}(1-d^{\mathrm{NB}}))}{\partial x}\right)^2} \times \frac{\partial d^{\mathrm{NB}}}{\partial r} - MMS$$

rearranging, we find that

$$\frac{\partial d^{\mathrm{NB}}}{\partial r} = MMS \times \left(1 - \frac{\frac{b}{1-b} \times \frac{\partial^2 \log \Delta\Pi\left(p_{\mathrm{list}}\left(1-d^{\mathrm{NB}}\right)\right)}{\partial x^2}}{\left(\frac{\partial \log \Delta\Pi(p_{\mathrm{list}}(1-d^{\mathrm{NB}}))}{\partial x}\right)^2}\right)^{-1} > 0$$

as long as $\frac{\partial^2 \log \Delta\Pi\left(p_{\mathrm{list}}\left(1-d^{\mathrm{NB}}\right)\right)}{\partial x^2} \leq 0$.

This proves the first part of the proposition. Since $\frac{\partial d^{\mathrm{NB}}}{\partial r}$ is a linear function of MMS with positive slope, the second part of the proposition also follows. □

B.2 Proof of Corollary 1

Proof. From Proposition 1 we know that the discount rate is increasing in r, and increasingly so for drugs with higher MMS. Because list price is fixed, the same applies to the net price on the commercial market, and since demand is perfectly inelastic, the same applies to revenue. □

B.3 Elastic Demand for Drugs

We first relax the assumption that demand for drugs is perfectly inelastic. We keep all other assumptions. Denote demand in the commercial market as $D_C\left(p_{\mathrm{list}}\left(1-d\right)\right)$ and demand in the Medicaid market as $D_M(p_M)$. p_M is still set through the formula

$$p_M = \min\left(p^0_{\mathrm{list}}, p_{\mathrm{list}}\right) - p_{\mathrm{list}} \times \max\left(r, d\right)$$

where p^0_{list} is the list price of the drug at launch, and r is a mandatory rebate.

The new problem can be stated as

$$\max_{d}\left[p_{\text{list}}\left(1-d\right)D_{C}\left(p_{\text{list}}\left(1-d\right)\right)-p_{\text{list}}\min\left\{0,d-r\right\}D_{M}\left(\min\left(p^{0}_{\text{list}},p_{\text{list}}\right)-p_{\text{list}}\times\max\left(r,d\right)\right)\right]^{b}$$
$$\times\left[\Pi\left(p_{\text{list}}\left(1-d\right)\right)-\Pi_{0}\right]^{1-b}$$

We assume that the profit function of the firm is concave (this assumption is implicitly satisfied when demand is perfectly inelastic). The first order condition of this new problem yields the following implicit expression for the equilibrium discount rate $d^{\text{NB,el}}$:

$$1-d^{\text{NB,el}}=\begin{cases}\frac{1}{\frac{\partial\log\left(D_{C}(\cdot)+D_{M}(\cdot)\right)}{\partial d}+\frac{(1-b)}{b}\frac{\partial\log\Delta\Pi(\cdot)}{\partial d}} & \text{if } d^{\text{NB,el}}\leq r\\ \frac{1}{\frac{\partial\log\left(D_{C}(\cdot)+D_{M}(\cdot)\right)}{\partial d}+\frac{(1-b)}{b}\frac{\partial\log\Delta\Pi(\cdot)}{\partial d}}+(1-r)\times MMS\left(\cdot\right)\times G\left(\cdot\right) & \text{if } d^{\text{NB,el}}>r\end{cases} \tag{2}$$

where the extra term $G\left(\cdot\right)$ is

$$G\left(d\right)=\frac{\frac{(1-b)}{b}\frac{\partial\log\Delta\Pi(\cdot)}{\partial d}+\frac{\frac{\partial D_{M}(\cdot)}{\partial d}}{D_{M}(\cdot)}}{\frac{\partial\log\left(D(\cdot)+D_{M}(\cdot)\right)}{\partial d}+\frac{(1-b)}{b}\frac{\partial\log\Delta\Pi(\cdot)}{\partial d}}$$

The term $G\left(d\right)$ also represents the difference of this FOC relative to the one we derived for the model in the main text of the article. We consider now the Proposition and Corollary proved in the main text.

Proposition 1. *The equilibrium discount rate $d^{NB,el}$ is weakly increasing in r, at a rate that is increasing in the Medicaid Market Share.*

Proof. We differentiate the FOC from Equation 2 with respect to r. The FOC of the first arm, where r does not appear directly, implies $\frac{\partial d^{\text{NB,el}}}{\partial r}=0$. We concentrate on the second arm.

First, notice that since the equilibrium bargaining discount is higher than the monopoly discount, we know that the derivative of the profit function of the manufacturer, evaluated at $d^{\text{NB,el}}$, is negative. In other words, decreasing the discount relative to the equilibrium level $d^{\text{NB,el}}$ leads to higher profits. The exact inequality implied by this condition is

$$\left(1-d^{\text{NB,el}}\right)\frac{\partial D_{C}}{\partial d}\left(d^{\text{NB,el}}\right)-\left(D_{C}\left(d^{\text{NB,el}}\right)+D_{M}\left(d^{\text{NB,el}}\right)\right)-\left(d^{\text{NB,el}}-r\right)\frac{\partial D_{M}}{\partial d}\left(d^{\text{NB,el}}\right)\leq 0 \tag{3}$$

where (with a slight abuse of notation) we have written all functions simply in terms of $d^{\text{NB,el}}$, since that is the variable of interest. Keeping this notation, we proceed to the proof.

Instead of differentiating the expression we derived for $1-d$, we go back to the original, non-simplified FOC, which is easier to manage. After applying a log transformation to the objective function, we obtain the following problem:

$$\max_{d} b \times \log\left(p_{\text{list}}\left(1-d\right) D_C\left(d\right) - p_{\text{list}}\left(d-r\right) D_M\left(d\right)\right) + \left(1-b\right) \times \log\left(\Pi\left(d\right) - \Pi_0\right)$$

The FOC of this problem implies the following condition for the equilibrium discount rate (all functions are evaluated at $d^{\text{NB,el}}$):

$$\frac{-D_C\left(\cdot\right) + \left(1-d^{\text{NB,el}}\right)\frac{\partial D_C}{\partial d}\left(\cdot\right) - D_M\left(\cdot\right) - \left(d^{\text{NB,el}}-r\right)\frac{\partial D_M}{\partial d}\left(\cdot\right)}{\left(1-d^{\text{NB,el}}\right) D_C\left(\cdot\right) - \left(d^{\text{NB,el}}-r\right) D_M\left(\cdot\right)} + \frac{\left(1-b\right)}{b}\frac{\frac{\partial \Pi}{\partial d}\left(\cdot\right)}{\Pi\left(\cdot\right) - \Pi_0} = 0$$

Let $d^{\text{NB,el}}\left(r\right)$ be the implicit function of the bargaining outcome with respect to the mandatory rebate. Implicitly differentiating with respect to r we get

$$\begin{aligned}
&-\frac{\left[\left(1-d^{\text{NB,el}}\right)\frac{\partial D_C}{\partial d}\left(\cdot\right) - \left(D_M\left(\cdot\right) + D_C\left(\cdot\right)\right) - \left(d^{\text{NB,el}}-r\right)\frac{\partial D_M}{\partial d}\left(\cdot\right)\right]}{\left[\left(1-d^{\text{NB,el}}\right) D_C\left(\cdot\right) - \left(d^{\text{NB,el}}-r\right) D_M\left(\cdot\right)\right]^2} D_M\left(\cdot\right) \\
&\qquad + \frac{\frac{\partial D_M}{\partial d}\left(\cdot\right)}{\left(1-d^{\text{NB,el}}\right) D_C\left(\cdot\right) - \left(d^{\text{NB,el}}-r\right) D_M\left(\cdot\right)} = \\
&\frac{\left(2\frac{\partial D_C}{\partial d}\left(\cdot\right) - \left(1-d^{\text{NB,el}}\right)\frac{\partial^2 D_C}{\partial d^2}\left(\cdot\right) + 2\frac{\partial D_M}{\partial d}\left(\cdot\right) + \left(d^{\text{NB,el}}-r\right)\frac{\partial^2 D_M}{\partial d^2}\left(\cdot\right)\right)}{\left(1-d^{\text{NB,el}}\right) D_C\left(\cdot\right) - \left(d^{\text{NB,el}}-r\right) D_M\left(\cdot\right)}\frac{\partial d^{\text{NB,el}}}{\partial r} + \\
&\frac{\left[\left(1-d^{\text{NB,el}}\right)\frac{\partial D_C}{\partial d}\left(\cdot\right) - \left(D_M\left(\cdot\right) + D_C\left(\cdot\right)\right) - \left(d^{\text{NB,el}}-r\right)\frac{\partial D_M}{\partial d}\left(\cdot\right)\right]^2}{\left[\left(1-d^{\text{NB,el}}\right) D_C\left(\cdot\right) - \left(d^{\text{NB,el}}-r\right) D_M\left(\cdot\right)\right]^2}\frac{\partial d^{\text{NB,el}}}{\partial r} + \\
&\qquad - \frac{\left(1-b\right)}{b}\frac{\frac{\partial^2 \Pi}{\partial d^2}\left(\cdot\right) \times \left(\Pi\left(\cdot\right) - \Pi_0\right) - \left(\frac{\partial \Pi}{\partial d}\left(\cdot\right)\right)^2}{\Pi\left(\cdot\right) - \Pi_0}\frac{\partial d^{\text{NB,el}}}{\partial r}
\end{aligned} \tag{4}$$

Consider each piece. On the left-hand side we have only positive terms. The first term is positive because the numerator is positive, by the condition derived in Equation 3. The second term is also positive because the numerator is positive (demand increases with the discount rate). On the right-hand side, we also have all positive terms. The first term is positive because its numerator is the opposite (in sign) of the second derivative of the profit function, which itself is negative as long as the profit function is concave, while its denominator is positive. The second term is clearly positive since it's a squared number. Finally, the third term is also a sum of positive numbers. Hence, the left-hand side of this equation is a positive linear function of $\frac{\partial d^{\text{NB,el}}}{\partial r}$. We conclude that $\frac{\partial d^{\text{NB,el}}}{\partial r} > 0$ as it is equal to the ratio of two positive numbers. This concludes the first part of the proof.

For the second part of the proof, we need to consider how the Medicaid market share enters the equation. In order to figure out its impact, we must rewrite the expression for $\frac{\partial d^{\text{NB,el}}}{\partial r}$ as a function of

$$MMS\left(d^{\text{NB,el}}\right) = \frac{D_M\left(d^{\text{NB,el}}\right)}{D_C\left(d^{\text{NB,el}}\right) + D_M\left(d^{\text{NB,el}}\right)}$$

and

$$MS\left(d^{\text{NB,el}}\right) = D_C\left(d^{\text{NB,el}}\right) + D_M\left(d^{\text{NB,el}}\right)$$

where $MS(\cdot)$ stands for market size. The idea is to check what happens to $\frac{\partial d^{\text{NB,el}}}{\partial r}$ as we shift $MMS\left(d^{\text{NB,el}}\right)$ while holding $MS\left(d^{\text{NB,el}}\right)$ constant. Since the expression for $\frac{\partial d^{\text{NB,el}}}{\partial r}$ is quite convoluted, it is easier to examine the numerator and the denominator of the implied ratio separately. First, notice that we can multiply both sides of Equation 4 by

$$\left[\left(1 - d^{\text{NB,el}}\right) D_C\left(d^{\text{NB,el}}\right) - \left(d^{\text{NB,el}} - r\right) D_M\left(d^{\text{NB,el}}\right)\right]^2$$

to simplify the algebra. Having done that, and after some manipulation, the numerator of the expression for $\frac{\partial d^{\text{NB,el}}}{\partial r}$ can be reduced to

$$\begin{aligned}
&MS\left(d^{\text{NB,el}}\right) \times \\
&\left[\left(MS\left(d^{\text{NB,el}}\right) - \left(1 - d^{\text{NB,el}}\right)\left(\frac{\partial MS}{\partial d}\left(d^{\text{NB,el}}\right)\right)\right) MMS\left(d^{\text{NB,el}}\right) + \left(1 - d^{\text{NB,el}}\right)\frac{\partial D_M}{\partial d}\left(d^{\text{NB,el}}\right)\right]
\end{aligned}$$

This is a positive linear function of MMS (it's easy to show that the number multiplying $MMS\left(d^{\text{NB,el}}\right)$ is positive using the result from Equation 4). Hence increasing the MMS leads to higher values of the numerator for the expression of $\frac{\partial d^{\text{NB,el}}}{\partial r}$.

Next, consider the denominator. After some manipulation, we can express it as

$$\begin{aligned}
A\left(d^{\text{NB,el}}\right)\left[\left(1 - d^{\text{NB,el}}\right) MS\left(d^{\text{NB,el}}\right) - (1-r)\, MMS\left(d^{\text{NB,el}}\right) MS\left(d^{\text{NB,el}}\right)\right] + B\left(d^{\text{NB,el}}\right) + \\
C\left(d^{\text{NB,el}}\right)\left[\left(1 - d^{\text{NB,el}}\right) MS\left(d^{\text{NB,el}}\right) - (1-r)\, MMS\left(d^{\text{NB,el}}\right) MS\left(d^{\text{NB,el}}\right)\right]^2
\end{aligned}$$

where

$$\begin{aligned}
A\left(d^{\text{NB,el}}\right) =& 2\frac{\partial D_C}{\partial d}\left(d^{\text{NB,el}}\right) - \left(1 - d^{\text{NB,el}}\right)\frac{\partial^2 D_C}{\partial d^2}\left(d^{\text{NB,el}}\right) + 2\frac{\partial D_M}{\partial d}\left(d^{\text{NB,el}}\right) \\
&+ \left(d^{\text{NB,el}} - r\right)\frac{\partial^2 D_M}{\partial d^2}\left(d^{\text{NB,el}}\right) \\
B\left(d^{\text{NB,el}}\right) =& \left[\left(1 - d^{\text{NB,el}}\right)\frac{\partial D_C}{\partial d}\left(d^{\text{NB,el}}\right) - MS\left(d^{\text{NB,el}}\right) - \left(d^{\text{NB,el}} - r\right)\frac{\partial D_M}{\partial d}\left(d^{\text{NB,el}}\right)\right]^2 \\
C\left(d^{\text{NB,el}}\right) =& -\frac{(1-b)}{b}\frac{\frac{\partial^2 \Pi}{\partial d^2}\left(d^{\text{NB,el}}\right) \times \left(\Pi\left(d^{\text{NB,el}}\right) - \Pi_0\right) - \left(\frac{\partial \Pi}{\partial d}\left(d^{\text{NB,el}}\right)\right)^2}{\Pi\left(d^{\text{NB,el}}\right) - \Pi_0}
\end{aligned}$$

are positive and do not depend on $MMS\left(d^{\text{NB,el}}\right)$. $MMS\left(d^{\text{NB,el}}\right)$ enters this equation in two parts, both with a negative sign. In the first, it enters linearly, so it clearly has a negative effect. In the second, it enters inside of a square term. This could be a problem if the expression inside of the square were negative (because in that case $MMS\left(d^{\text{NB,el}}\right)$ would increase its absolute value). However, the square term is strictly positive (it's the expression for total firm revenue), therefore the impact of $MMS\left(d^{\text{NB,el}}\right)$ is negative here as well.

Hence, increasing $MMS\left(d^{\text{NB,el}}\right)$ has a positive impact on $\frac{\partial d^{\text{NB,el}}}{\partial r}$. This proves the second statement of the proposition. □

Corollary 2. *Total firm revenue from the commercial market is weakly decreasing in r, at a rate that is increasing in the Medicaid Market Share.*

This Corollary follows from Proposition 1. When r increases, the equilibrium discount rate (weakly) increases. Combined with fixed list prices, the change will lower the equilibrium net price. Since the equilibrium price is below the monopoly price, total revenue will also decrease.

B.4 Endogenous List Prices

Next, we relax the assumption that the list price is exogenous. We still leave p^0_{list} as exogenously fixed. Our model refers to firms that experience a change in r after having launched. Hence, the assumption is valid as long as the firm did not expect the change in r.

In this generalized version of the model we need a way to pin down p_{list} separately from d. We do this by assuming that the list price affects some part of the revenue function of the firm.[6] We model this additional revenue as a reduced form function $R\left(p_{\text{list}}\right)$ which enters the firm overall profit function additively. We also assume that if the firm does not reach an agreement with the commercial payer it can charge whatever p_{list} maximizes $R\left(p_{\text{list}}\right)$. To simplify the algebra, we revert to the original assumption of inelastic Medicaid and commercial demand.

We start by establishing a baseline p_{list} and d. Let $p^{R'}_{\text{list}}$ be the price that maximizes the profits if the negotiation fails. In other words,

$$p^{R'}_{\text{list}} = \arg\max_{p_{\text{list}}} R\left(p_{\text{list}}\right) + \left(\min\left(p^0_{\text{list}}, p_{\text{list}}\right) - p_{\text{list}} \times r\right) D_M$$

Hence, $p^{R'}_{\text{list}}$ satisfies

$$R'\left(p^{R'}_{\text{list}}\right) + \frac{\partial p_M}{\partial p_{\text{list}}} D_M = 0$$

To make things simpler, we assume that the optimal list price is greater than p^0_{list} (this is the empirically relevant case, since list prices tend to grow over time). Hence, $\frac{\partial p_M}{\partial p_{\text{list}}} = -r$, and the condition implies

$$R'\left(p^{R'}_{\text{list}}\right) - r \times D_M = 0$$

[6] There are many ways to justify this. For example, some consumers pay a fraction of the list price (e.g. Medicare patients in the donut hole, uninsured patients). Other benefits of a high list price include the ability to better price discriminate across various commercial payers, which in our model does not arise since we have a single representative payer.

Crucially, this implies that, as long as R' is concave, $p_{\text{list}}^{R'} < p_{\text{list}}^{R}$.

Now we are ready to consider the full problem of the manufacturer (after a log transformation):

$$\max_{p_{\text{list}},d} b \times \log\left(R\left(p_{\text{list}}\right) + p_{\text{list}}\left(1-d\right)D_C - \max\left\{d,r\right\}p_{\text{list}}D_M - R\left(p_{\text{list}}^{R'}\right) + rp_{\text{list}}^{R'}D_M\right) \\ + \left(1-b\right) \times \log\left(\Pi\left(p_{\text{list}}\left(1-d\right)\right) - \Pi_0\right)$$

The problem has two first order conditions, which imply, respectively:

$$p_{\text{list}}^{\text{NB}} = \begin{cases} \dfrac{1+\frac{R'(p_{\text{list}})}{(1-d)D_C - rD_M}}{-\frac{1-b}{b}\times\frac{(1-d)\Pi'(p_{\text{list}}(1-d))}{\Pi(p_{\text{list}}(1-d))-\Pi_0}} - \dfrac{\left(R(p_{\text{list}})-R\left(p_{\text{list}}^{R'}\right)\right)+p_{\text{list}}^{R'}rD_M}{(1-d)D_C - rD_M} & \text{if } d \le r \\ \dfrac{1+\frac{R'(p_{\text{list}})}{(1-d)D_C - dD_M}}{-\frac{1-b}{b}\times\frac{(1-d)\Pi'(p_{\text{list}}(1-d))}{\Pi(p_{\text{list}}(1-d))-\Pi_0}} - \dfrac{\left(R(p_{\text{list}})-R\left(p_{\text{list}}^{R'}\right)\right)-p_{\text{list}}^{R'}rD_M}{(1-d)D_C - dD_M} & \text{if } d > r \end{cases}$$

and

$$1-d^{\text{NB}} = \begin{cases} \dfrac{-1}{\frac{1-b}{b}\times\frac{p_{\text{list}}\Pi'(p_{\text{list}}(1-d))}{\Pi(p_{\text{list}}(1-d))-\Pi_0}} - \dfrac{\left(R(p_{\text{list}})-R\left(p_{\text{list}}^{R'}\right)\right)-r\left(p_{\text{list}}-p_{\text{list}}^{R'}\right)D_M}{p_{\text{list}}D_C} & \text{if } d \le r \\ \dfrac{-1}{\frac{1-b}{b}\times\frac{p_{\text{list}}\Pi'(p_{\text{list}}(1-d))}{\Pi(p_{\text{list}}(1-d))-\Pi_0}} - \dfrac{\left(R(p_{\text{list}})-R\left(p_{\text{list}}^{R'}\right)\right)-\left(p_{\text{list}}-rp_{\text{list}}^{R'}\right)D_M}{p_{\text{list}}(D_C+D_M)} & \text{if } d > r \end{cases}$$

We start the analysis of this model by proving two Lemmas about the equilibrium list price.

Lemma 3. *If $d^{NB} \le r$, then the optimal solution is to set $p_{list}^{NB} = p_{list}^{R'}$.*

Proof. To prove this lemma, we take the FOCs for the case $d^{\text{NB}} \le r$, and show that they are satisfied by setting $p_{\text{list}}^{\text{NB}} = p_{\text{list}}^{R'}$. Starting from

$$p_{\text{list}}^{\text{NB}} = \frac{1+\frac{R'(p_{\text{list}})}{(1-d)D_C - rD_M}}{-\frac{1-b}{b}\times\frac{(1-d)\Pi'(p_{\text{list}}(1-d))}{\Pi(p_{\text{list}}(1-d))-\Pi_0}} - \frac{\left(R\left(p_{\text{list}}\right)-R\left(p_{\text{list}}^{R'}\right)\right)+p_{\text{list}}^{R'}rD_M}{\left(1-d\right)D_C - rD_M}$$

$$1-d^{\text{NB}} = \frac{-1}{\frac{1-b}{b}\times\frac{p_{\text{list}}\Pi'(p_{\text{list}}(1-d))}{\Pi(p_{\text{list}}(1-d))-\Pi_0}} - \frac{\left(R\left(p_{\text{list}}\right)-R\left(p_{\text{list}}^{R'}\right)\right)-r\left(p_{\text{list}}-p_{\text{list}}^{R'}\right)D_M}{p_{\text{list}}D_C}$$

plug in $p_{\text{list}}^{\text{NB}} = p_{\text{list}}^{R'}$ and obtain

$$\begin{aligned} p_{\text{list}}^{\text{NB}} &= \frac{1 + \frac{rD_M}{(1-d)D_C - rD_M}}{-\frac{1-b}{b} \times \frac{(1-d)\Pi'\left(p_{\text{list}}^{R'}(1-d)\right)}{\Pi\left(p_{\text{list}}^{R'}(1-d)\right) - \Pi_0}} - \frac{p_{\text{list}}^{R'} rD_M}{(1-d)\,D_C - rD_M} \\ 1 - d^{\text{NB}} &= \frac{-1}{\frac{1-b}{b} \times \frac{p_{\text{list}}^{R'}\Pi'\left(p_{\text{list}}^{R'}(1-d)\right)}{\Pi\left(p_{\text{list}}^{R'}(1-d)\right) - \Pi_0}} \end{aligned}$$

where we used the fact that $R'\left(p_{\text{list}}^{R'}\right) = rD_M$. At this point, substitute the second condition into the first one:

$$\begin{aligned} p_{\text{list}}^{\text{NB}} &= \left(1 + \frac{rD_M}{(1-d)\,D_C - rD_M}\right) \frac{p_{\text{list}}^{R'}}{1 - d^{\text{NB}}} \left(1 - d^{\text{NB}}\right) - \frac{p_{\text{list}}^{R'} rD_M}{(1-d)\,D_C - rD_M} \\ \implies p_{\text{list}}^{\text{NB}} &= \left(1 + \frac{rD_M}{(1-d)\,D_C - rD_M}\right) p_{\text{list}}^{R'} - \frac{p_{\text{list}}^{R'} rD_M}{(1-d)\,D_C - rD_M} \\ \implies p_{\text{list}}^{\text{NB}} &= p_{\text{list}}^{R'} \end{aligned}$$

This concludes the proof. □

Lemma 4. *If $d^{NB} > r$, then the optimal solution is to set $p_{list}^{NB} \leq p_{list}^{R'}$.*

Proof. We can prove this statement using a simple intuitive argument. Suppose that the optimal list price is $p_{\text{list}}^{\text{NB}} > p_{\text{list}}^{R'}$, and let the optimal discount rate be $d^{\text{NB}} > r$. Then, consider the following deviation, where we keep $p_{\text{list}}^{\text{NB}}\left(1 - d^{\text{NB}}\right)$ constant, but lower both p_{list} and d marginally.

The profit function of the firm in this situation is

$$R\left(p_{\text{list}}^{\text{NB}}\right) + p_{\text{list}}^{\text{NB}}(1-d)\,D_C - d^{\text{NB}} p_{\text{list}}^{\text{NB}} D_M - R\left(p_{\text{list}}^{R'}\right) + r p_{\text{list}}^{R'} D_M$$

Since we are keeping $p_{\text{list}}^{\text{NB}}\left(1 - d^{\text{NB}}\right)$ constant, we only need to consider the impact of this deviation on $R\left(p_{\text{list}}^{\text{NB}}\right) - d^{\text{NB}} p_{\text{list}}^{\text{NB}} D_M$. By lowering p_{list} marginally, the firm gains $d^{\text{NB}} D_M$ marginally. Since we know that

$$R'\left(p_{\text{list}}^{R'}\right) = r \times D_M$$

and that R is concave, we also know that the firm will lose strictly less than rD_M, marginally, from the function $R(\cdot)$. Since $d^{\text{NB}} > r$, this is a net gain in profit. This concludes the proof of the proposition.[7] □

We are now ready to prove the main results from the paper.

Proposition 5. *The equilibrium discount rate d^{NB} is weakly increasing in r, at a rate that is increasing in the Medicaid Market Share.*

[7] The firm also has an additional marginal gain of $p_{\text{list}} \times D_M$ from lowering d which further increases their net gain from this deviation.

Proof. As always, we consider the two arms separately. From Lemma 3 we know that if $d^{\text{NB}} \leq r$, then $p_{\text{list}} = p_{\text{list}}^{R'}$. Hence, we have the following FOC for d^{NB} :

$$1 - d^{\text{NB}} = \frac{-1}{\frac{1-b}{b} \times \frac{p_{\text{list}}\Pi'(p_{\text{list}}(1-d))}{\Pi(p_{\text{list}}(1-d))-\Pi_0}}$$

This condition is identical to the ones in all previous models, and yields $\frac{\partial d^{\text{NB}}}{\partial r} = 0$.

Next, we consider the second arm. From Lemma 4 we know that if $d^{\text{NB}} > r$, then $p_{\text{list}} \leq p_{\text{list}}^{R'}$. Consider the FOC, slightly rearranged:

$$1 - d^{\text{NB}} = \frac{1}{\frac{1-b}{b} \times \frac{\partial \Delta\Pi(p_{\text{list}}(1-d))}{\partial d}} + \frac{R\left(p_{\text{list}}^{R'}\right) - R\left(p_{\text{list}}\right)}{p_{\text{list}}\left(D_C + D_M\right)} + \left(1 - r\frac{p_{\text{list}}^{R'}}{p_{\text{list}}}\right) MMS$$

We differentiate with respect to r:

$$\begin{aligned} -\frac{\partial d^{\text{NB}}}{\partial r} = & -\frac{\frac{1-b}{b} \times \frac{\partial^2 \Delta\Pi(p_{\text{list}}(1-d))}{\partial d^2}\frac{\partial d^{\text{NB}}}{\partial r}}{\left(\frac{1-b}{b} \times \frac{\partial \Delta\Pi(p_{\text{list}}(1-d))}{\partial d}\right)^2} + \\ & \frac{-R'\left(p_{\text{list}}\right)\frac{\partial p_{\text{list}}}{\partial r}\left(p_{\text{list}}\left(D_C + D_M\right)\right) - \left(R\left(p_{\text{list}}^{R'}\right) - R\left(p_{\text{list}}\right)\right)\frac{\partial p_{\text{list}}}{\partial r}\left(D_C + D_M\right)}{\left(p_{\text{list}}\left(D_C + D_M\right)\right)^2} \\ & - \frac{p_{\text{list}} - r\frac{\partial p_{\text{list}}}{\partial r}}{p_{\text{list}}^2} p_{\text{list}}^{R'} MMS \end{aligned}$$

Isolate all terms that multiply $\frac{\partial d^{\text{NB}}}{\partial r}$ to get

$$\begin{aligned} & \underbrace{\frac{p_{\text{list}}^{R'}}{p_{\text{list}}} MMS +}_{\geq 0} \\ & \underbrace{\left(-\frac{r}{p_{\text{list}}^2} - \frac{-R'\left(p_{\text{list}}\right)\left(p_{\text{list}}\left(D_C + D_M\right)\right) - \left(R\left(p_{\text{list}}^{R'}\right) - R\left(p_{\text{list}}\right)\right)\left(D_C + D_M\right)}{\left(p_{\text{list}}\left(D_C + D_M\right)\right)^2}\right)}_{\leq 0} \frac{\partial p_{\text{list}}}{\partial r} = \\ & \underbrace{\left(1 - \frac{\frac{1-b}{b} \times \frac{\partial^2 \Delta\Pi(p_{\text{list}}(1-d))}{\partial d^2}}{\left(\frac{1-b}{b} \times \frac{\partial \Delta\Pi(p_{\text{list}}(1-d))}{\partial d}\right)^2}\right)}_{\geq 0} \frac{\partial d^{\text{NB}}}{\partial r} \end{aligned}$$

We use result from Lemma 4 ($p_{\text{list}}^{\text{NB}} < p_{\text{list}}^{R}$) to show that the term multiplying $\frac{\partial p_{\text{list}}}{\partial r}$ is negative. Hence, the first result of our proposition is true as long as $\frac{\partial p_{\text{list}}}{\partial r} < 0$.[8] This proves the first part of

[8]Lemma 4, while not a proof of this statement, suggests that this is the case, since $p_{\text{list}}^{\text{NB}}$ falls below optimal levels when $d^{\text{NB}} > r$. Intuitively, as r increases, the penalty for setting a high p_{list} increases (under the assumption that the

the Proposition.

For the second part, notice that MMS enters the expression for $\frac{\partial d^{\mathrm{NB}}}{\partial r}$ only once, in the numerator, and with a positive sign. Hence, when MMS goes up, so does $\frac{\partial d^{\mathrm{NB}}}{\partial r}$. This concludes the proof. □

Corollary 6. *Total firm revenue from the commercial market is weakly decreasing in r, at a rate that is increasing in the Medicaid Market Share.*

This Corollary follows from Proposition 5. When r increases, the equilibrium discount rate (weakly) increases. Combined with inelastic demand, the change will lower the equilibrium net price as long as $\frac{\partial p_{\mathrm{list}}}{\partial r} < 0$ (the same assumption we used in proving the previous corollary).

current p_{list} is above the initial list price). The comparative static is also backed by our empirical analysis. We omit a more complete proof of this statement.

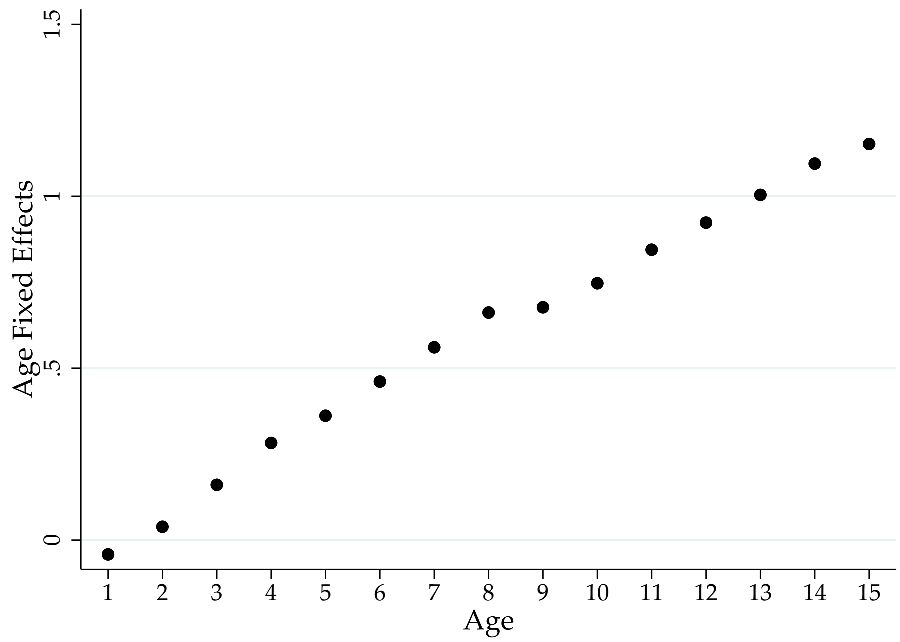


Figure A1: Age fixed effects for WAC regression (Core Sample)

C Additional Empirical Results

This section presents and discusses additional empirical results not covered in the main text.

C.1 Age Fixed Effects

Figures A1, A1, and A1 report the pattern of age fixed effects associated with estimates of Equation 8 with WAC (log), non-Medicaid discount, and non-Medicaid revenue (log) as the outcomes, respectively.

WAC and non-Medicaid discounts appear to grow at a roughly linear rate over the lifecycle of a drug. Log net non-Medicaid revenue exhibits an inverted-U shape, consistent with existing literature that models lifecycle effects using quadratic age controls. Revenue grows initially as the drug diffuses, and then decreases as additional competitors enter.

Adding age FE only has a major impact on the revenue results. High MMS drugs in the core sample are slightly older, and some may naturally be declining in revenue. This can cause an incorrect inference that the rule change causes a decline in revenue for high MMS drugs. Incorporating age FE controls for this mechanical relationship, isolating deviations from the secular trends.

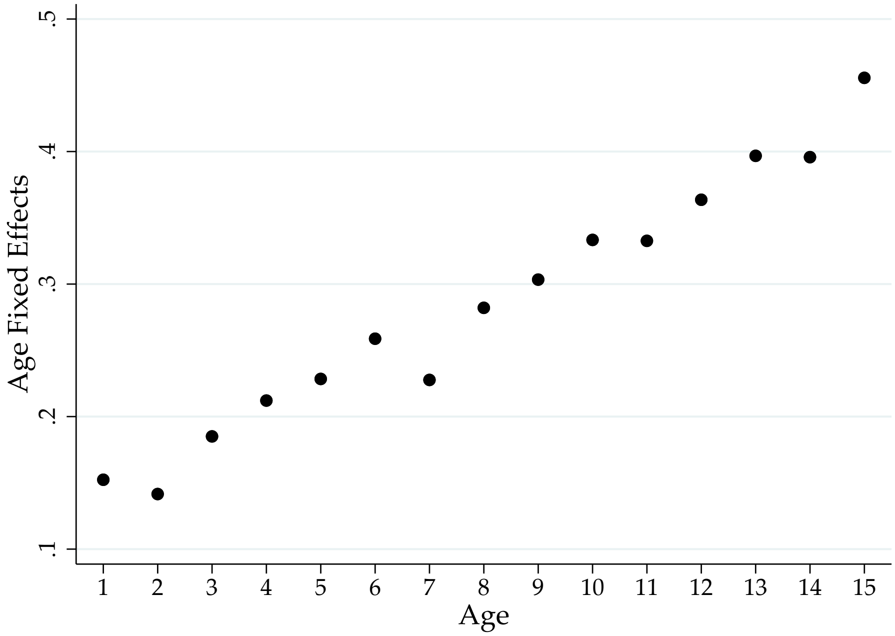


Figure A2: Age fixed effects for non-Medicaid discount regression (Core Sample)

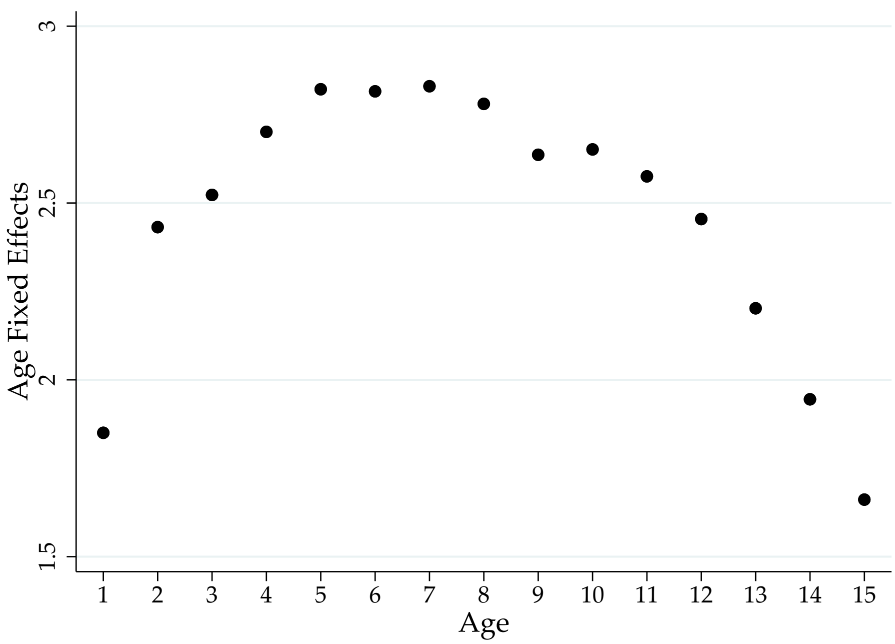


Figure A3: Age fixed effects for log net non-Medicaid revenue regression (core sample)

C.2 *Medicaid Discount Correction*

As noted in the main text, we cannot observe when the Medicaid MFCC takes effect. This problem creates measurement error in the "Net Non-Medicaid Revenue" variable. To test the robustness of our specification to this kind of measurement error we repeat the analysis using the average non-Medicaid discount in the data as the "best price". Under this assumption, the Medicaid rebate, net non-Medicaid revenue, and non-Medicaid discount are simultaneously determined by the following three equations, where the unknowns are in bold and the rest are data or known parameters:

$$\textbf{Medicaid Rebate}_{jt} = \max\left(r_{jt}, \boldsymbol{d_{jt}^{\text{non-Med}}}\right) + \text{Inflation Penalty}_{jt}$$

$$\textbf{Net Non-Medicaid Revenue}_{jt} = \text{Net sales}_{jt} - \text{Medicaid sales}_{jt} \times \left(1 - \textbf{Medicaid Rebate}_{jt}\right)$$

$$\boldsymbol{d_{jt}^{\text{non-Med}}} = 1 - \frac{\textbf{Net Non-Medicaid Revenue}_{jt}}{\text{Invoice sales}_{jt} - \text{Medicaid sales}_{jt}}$$

We use an iterative fixed-point procedure to find the quantities that simultaneously satisfy the three equations. We start with the Medicaid rebate from the SSR data, and iterate through the three equations, updating the LHS quantity. Medicaid sales data again comes from the Centers for Medicare and Medicaid Services (Centers for Medicare and Medicaid Services, 2019). The procedure stops when the difference across cycles is negligible. We also account for the post-2010 Medicaid rebate cap by capping implied Medicaid rebates at 100 percent after 2010.

Intuitively, for drugs with low net non-Medicaid revenue vs. invoice sales, the MFCC is assumed to take effect. We then adjust the Medicaid rebate upwards to take into account this fact, which increases the implied net non-Medicaid revenue. This has the effect of adjusting non-Medicaid discounts slightly downwards for these drugs, more so for high MMS drugs. For drugs with implied non-Medicaid discounts that are lower than the mandatory rebate, this procedure has no effect.

In general, the average discount would underestimate the best discount, especially if there is a lot of variance in what is offered to private payers. However, in this case the average could actually overestimate the best discount, because the non-Medicaid numbers include the VA, 340B, and Medicare Part D, which are likely to have higher discounts both for political and strategic reasons. In unreported results we also test the robustness of the results to using different multiples of the non-Medicaid discount as the best-price.

Table A3 reports the diff-in-diff estimates using the adjusted non-Medicaid discount data. The point estimates are statistically significant but smaller than the ones presented in the main text, albeit statistically indistinguishable. The likely explanation for this result is that underestimating Medicaid discounts is likely to be most problematic for drugs with high MMS in the pre-reform

Table A3: The Impact of the MDRP Change on Non-Medicaid Discounts (Medicaid Discount Correction)

	Non-Medicaid Discount					
Post ACA	0.0652	0.0479	0.0522**	0.00161	-0.0146	-0.0113
	(0.00959)	(0.0132)	(0.0114)	(0.0111)	(0.0123)	(0.0115)
MMS		0.240			0.224	
× Post-ACA		(0.125)			(0.117)	
High MMS Ind.			0.0485			0.0491
× Post-ACA			(0.0200)			(0.0198)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1061	1061	1061	1061	1061	1061

Notes: Estimates of Equation 8. Standard errors clustered at the drug level.

Table A4: Correlations of Observables and MMS (2009)

	Non-Med Discount	Age	Log(sales)	Log(WAC)
MMS 2009	-0.251	9.563	3.197	1.691
	(0.154)	(5.381)	(2.380)	(1.744)
N	196	198	198	198

Notes: Predicting 2009 outcomes using MMS. log(sales) refers to the log of invoice sales.

period. Mechanically, this error can make it seem like there is an increase in discounts for high MMS drugs after the rule change, even if there are no actual changes. However, as shown here, the effect still remains after accounting for this issue.[9]

C.3 Additional Medicaid Market Share Statistics

We provide additional evidence on the Medicaid Market Share (MMS) variable, focusing on its correlation with pre-ACA discounts and evolution over time.

First, we present evidence on the correlation between drug observables and MMS in 2009 in Table A4. The goal is to provide additional context into ways MMS could be proxying for other variables that might be associated with secular trends. All of the measured correlations are noisy, but MMS is associated with smaller non-Medicaid discounts, greater age, greater sales, and greater WAC, at least within the 2009 cross section. The magnitude of the correlation per standard deviation of MMS (0.08) is very small.

Second, we present evidence on the evolution of MMS over time. We regress our measure of

[9] We also attempt corrections by assuming that the best discount is some multiple of the average discount and find similar results.

Table A5: Drugs with Highest Medicaid Market Share (2009)

Drug Name	**Class**	**MMS**	**2009 Gross Sales ($M)**
DIASTAT / ACUDIAL	Epilepsy	0.524	94.9
DIURIL	Hypertension	0.406	0.5
INVEGA	Antipsychotic	0.358	319.3
PEPCID SUSPENSION	Ulcer	0.311	25.3
RITALIN / FOCALIN	ADHD	0.294	483.6
SEROQUEL XR	Antipsychotic	0.276	424.4
MOBAN	Antipsychotic	0.257	7.3
SEROQUEL IR	Antipsychotic	0.246	3916.5
CONCERTA	ADHD	0.238	1241.4
PULMICORT	COPD	0.230	899.2

MMS in a given year on our 2009 measure of MMS, which features prominently in our analysis, and report the results in Figure A4a. As noted in our discussion of data reliability, the correlation between 2008 and 2009 MMS is almost exactly 1. The coefficient for 2010 is 1.143. The jump is probably driven largely by the initial Medicaid expansion of a few states (most notably California) that occurred in 2010. The inclusion of Medicaid Managed Care in the sales numbers reported by CMS probably had a minor impact on the coefficient, as most states did not rely on managed care to handle drug benefits (Dranove et al., 2017). Finally, the estimated coefficient increases over time as there are additional expansions to Medicaid, rising to 1.4 in 2015.

Finally, we provide a sense of the drugs with high and low MMS. Overall, the drugs with high MMS are in classes treating HIV/AIDS, mental health conditions, and asthma. These correspond to diseases that are known to affect low-income individuals. Drugs with low MMS are in classes such as cardiovascular drugs, osteoporosis, and erectile dysfunction, all conditions that affect older individuals (many of whom are covered by Medicare). Table A5 presents basic information on the ten drugs in our core sample with the highest measure of MMS in 2009.

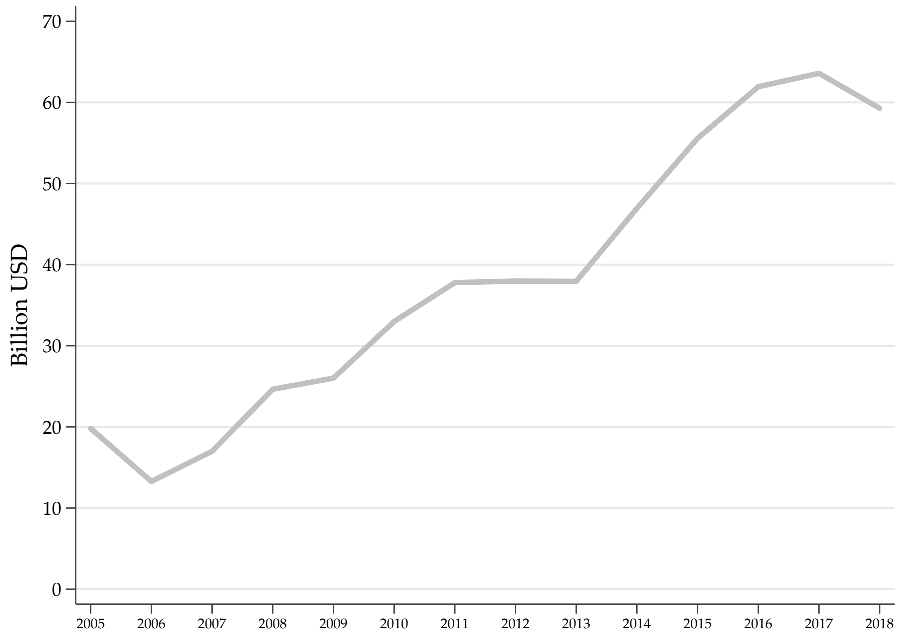
C.4 Launch Price Response

One potential response to the MDRP rule change we do not test for in the main text is adjustment of launch prices for new drugs. This is partly because using the sample of drugs already on the market allows us to cleanly test the implications of our model. In addition, launch price responses are difficult to identify, because of the low number of drug launches and difficulties in comparing unit prices across drugs in different markets.

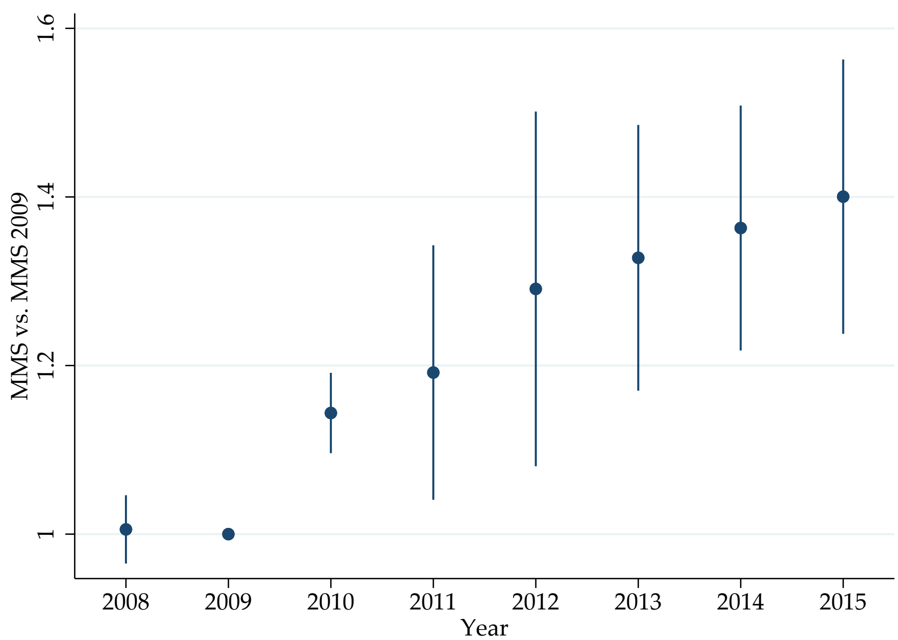
To provide some evidence on the launch price response, we run the following specification on the set of drugs launched between 2007 and 2012 that are tracked by SSR Health:

$$\log\left(WAC_i\right) = \beta_0 + \beta_1 \times MMS_i + \beta_2 \times \text{PostACA}_i + \beta_3 \times MMS_i \times \text{PostACA}_i + \varepsilon_i \tag{5}$$

where all variables are measured during the launch year and i indexes the drug. For some speci-



(a) Evolution of Medicaid invoice sales



(b) Evolution of MMS Over Time relative to 2009

Figure A4: Evolution of Medicaid Prescription Drug Statistics Over Time

Table A6: The Impact of the MDRP Change on Launch Prices

	log (WAC)			
MMS	-2.660	-0.392	4.322	2.258
	(2.997)	(5.339)	(3.257)	(4.580)
Post-ACA		1.423		0.0284
		(0.396)		(0.358)
MMS		-4.607		3.964
$\times$ Post-ACA		(6.293)		(6.396)
ATC-2 FE	N	N	Y	Y
N	182	182	159	159

Notes: Estimates of Equation 5 using drugs that launched between 2007 and 2012 and covered by the SSR Health data. All launch prices are adjusted for inflation (U.S. Bureau of Labor Statistics, 2021). ATC information is unavailable for a subset of the drugs in the full SSR sample. Standard errors clustered at the drug level.

fications, we include ATC-2 fixed effects, in order to try to compare drugs within similar disease areas. ATC information comes from Kury (2020).

Table A6 reports the results. We generally find very noisy results, with some suggestive evidence of higher launch list prices for high MMS drugs after the MDRP rule change when we compare within ATC-2 classes—though our estimated coefficients appear too large to be realistic. Within ATC-2 classes, higher MMS is weakly correlated with list prices at launch, consistent with findings in Duggan and Scott Morton (2006).

In results not reported here, we also repeat the analysis using the core, FHM, and KCC samples, in order to compare drugs sold through the retail channel. We find noisier results using these restricted samples, with differing qualitative estimates. In addition, we also expand the sample to include drugs that launch later. Overall, none of these tests provide definitive evidence of a launch price response to the MDRP rule change.

Table A7: The Impact of the MDRP Change on Non-Medicaid Quantities

	log(WAC)	log(Units)	log(1-Discount)	log(1-Raw Discount)	log(Revenue)
Post-ACA	0.0449	-0.0744	0.0152	0.0854	0.0559
	(0.0169)	(0.0977)	(0.0209)	(0.0386)	(0.108)
MMS	-0.400	-0.686	-0.443	-0.816	-1.901
$\times$ Post-ACA	(0.201)	(1.052)	(0.181)	(0.282)	(1.167)
Fixed Effects			Drug, Age		
N	1064	1064	1064	1064	1064

Notes: Estimates of Equation 8 with different outcome variables (all variables are non-Medicaid measures). Age refers to the number of years a drug has been on the market. For comparability, we restrict to data points where non-Medicaid revenue is positive but results are similar without the restriction. Standard errors are clustered at the drug level.

C.5 Non-Medicaid Revenue Effect Breakdown – WAC, Units, and Discounts

We provide a breakdown of the revenue effect presented in Table 4 of the main paper. The revenue response post rule change is about -16 percent per standard deviation of MMS, which is larger than the discount response.

The size of the coefficient is driven by three components. As an accounting identity,

$$\text{Non-Medicaid Revenue} = \text{WAC} \times (1 - \text{Non-Medicaid Discount}) \times \text{Units}$$

We then estimate Equation 8 with the log of each of these four quantities in order to break down the revenue effect.

Table A7 presents the results. The precisely estimated coefficient in Column 1 shows that about a quarter of the effect is driven by differences in list price dynamics. This likely reflects the incentives created by the inflation penalty. Column 2 reveals a noisy but negative impact on units. This accounts for another quarter of the overall effect, but is likely to be unreliable. The outcome in Column 3 is a transform of the winsorized discount variable analyzed in the main text. This shows that another quarter of the revenue effect is driven by changes in non-Medicaid negotiation outcomes. Column 4 uses the raw discount estimate and finds a coefficient that is double in size. Taking the sum of the coefficients in Columns 1, 2, and 4 yields a similar estimate to the coefficient in Column 5 (the estimate from the main text), with the discrepancy driven by minor sample differences.

The results suggest that the revenue effect is driven by three channels, all of which contribute to the size of the overall revenue estimate. The discrepancy between Columns 3 and 4 suggests that the results using the winsorized discount variable offer a conservative picture of the size of the revenue impact through the discount channel. However, the unwinsorized discount measure yields some implausible implied discounts, putting into question the reliability of the underlying data, which motivates our using the winsorized outcome in our core analysis.

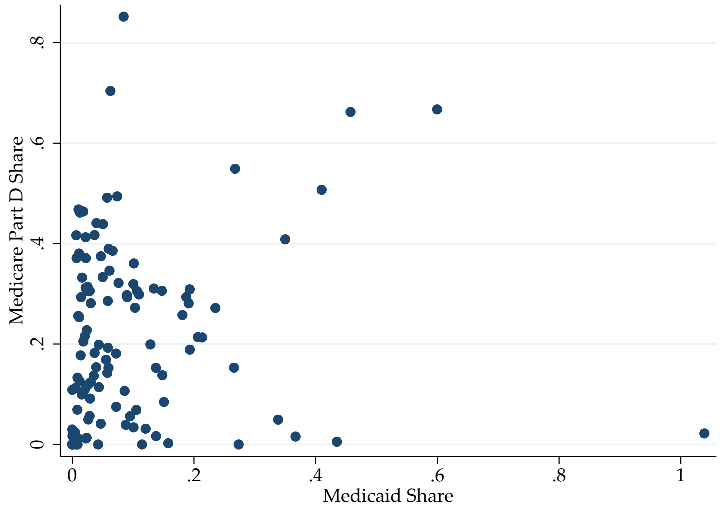


Figure A5: Relationship Between Medicare Part D and Medicaid Market Shares

Notes: Medicare Part D and Medicaid Market Shares are computed using 2012 gross sales data from the CMS Dashboard, combined with gross sales figures from SSR Health. Only drugs from our core sample are included.

C.6 Robustness Checks and Additional Results

Here, we report additional results within the framework of Equation 8 in the main body of the article.

Impact of Medicare Part D rule change

We start by addressing the potential issues created by the simultaneous Medicare Part D rule changes discussed in the main text. Using data from 2012, the first year in which CMS reports gross spending by drug through the CMS Dashboard (Centers for Medicare and Medicaid Services, 2016), we construct a Medicare Part D market share variable for the set of drugs in our core sample. Figure A5 shows a noisy but weakly positive relationship between Part D share and Medicaid share. This is slightly surprising given that the two programs serve people of different ages. However, this may partly be driven by the size of Medicare Part B, which is negatively correlated with both Part D share and Medicaid, the former due to Medicare coverage rules and the latter due to the fact that Part B drugs generally cover biologics that treat older individuals (e.g., cancer, arthritis).

We then formally control for potential Part D effects, by adding a term interacting Part D share with "Post-2011" to our core specification, capturing the 2011 change to Part D rules. This approach reduces the number of drugs in our sample by 52. These are drugs for which we cannot find corresponding entries in the CMS Dashboard data. Table A8 shows that this approach yields noisier but almost quantitatively identical estimates to those in our core specifications in terms of non-Medicaid discounts. Non-Medicaid revenue results become smaller in magnitude after

Table A9: The Impact of the MDRP Change on Non-Medicaid Net Price

	log (Non-Medicaid Net Price)					
Post ACA	0.143	0.218	0.194	0.000430	0.0766	0.0523
	(0.0297)	(0.0418)	(0.0359)	(0.0412)	(0.0478)	(0.0429)
MMS		-1.018			-1.024	
× Post-ACA		(0.377)			(0.352)	
High MMS Ind.			-0.187			-0.193
× Post-ACA			(0.0577)			(0.0557)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1024	1024	1024	1024	1024	1024

Notes: Estimates of Equation 8. The discrepancy in data points is driven by negative imputed net non-Medicaid sales. Standard errors clustered at the drug level.

adding the Part D controls.

Table A8: The Impact of the MDRP Change – Controlling for Part D Market Share

	Non-Medicaid Discount		*log*(Net Non-Med. Revenue)	
Part D Share	0.178	0.205	-0.339	-0.585
× Post-2011	(0.0651)	(0.0668)	(0.479)	(0.372)
MMS	0.237	0.261	-1.775	-0.807
× Post-ACA	(0.190)	(0.219)	(1.541)	(0.875)
Drug FE	Y	Y	Y	Y
Age FE	N	Y	N	Y
Year FE	Y	Y	Y	Y
N	676	676	674	674

Notes: Estimates of Equation 8, with the additional controls for Part D share. Standard errors clustered at the drug level.

Functional form assumptions

Next, we test the robustness of our estimates with respect to functional form assumptions. First, we confirm that the MDRP change leads to a lower non-Medicaid net price, reporting the results in Table A9. This is unsurprising, given that non-Medicaid discounts increase and list prices drop after the change. Second, we show that replacing the MMS variable with MMS quartiles leads to similar results. One concern noted in the main text is that MMS is noisily measured, and therefore drugs with misleadingly high or low MMS could end up driving our results.

Table A10: The Impact of the MDRP Change – Quartile Specifications

	Non-Medicaid Discount		log(Net Non-Medicaid Revenue)	
Post ACA	0.0620	-0.00488	0.0621	-0.0151
	(0.0163)	(0.0163)	(0.115)	(0.0848)
MMS Quartile 2	-0.0172	-0.0179	0.106	-0.00875
× Post-ACA	(0.0296)	(0.0294)	(0.177)	(0.155)
MMS Quartile 3	0.0464	0.0509	-0.253	-0.147
× Post-ACA	(0.0248)	(0.0255)	(0.180)	(0.136)
MMS Quartile 4	0.0345	0.0310	-0.487	-0.336
× Post-ACA	(0.0361)	(0.0348)	(0.404)	(0.361)
Drug FE	Y	Y	Y	Y
Age FE	N	Y	N	Y
N	1,067	1,067	1,064	1,064

Notes: Estimates of Equation 8, but with indicators for MMS quartile in place of the MMS variables. Standard errors clustered at the drug level.

Instead, Table A10 shows that the estimates using quartile variables are noisier but qualitatively and quantitatively similar results. Third, we check that our results are not driven by compositional issues across years, by replacing the "Post ACA" variable with a set of year fixed-effects. This will only matter if there are differences in composition of high and low MMS drugs across years. Table A11 shows that the results using year fixed-effects yield almost identical estimates to the ones reported in the main text.

Table A11: The Impact of the MDRP Change – Year Fixed Effects

	Non-Medicaid Discount				log(Net Non-Medicaid Revenue)			
MMS	0.265		0.259		-2.670		-1.907	
× Post-ACA	(0.135)		(0.127)		(1.368)		(1.173)	
High MMS Ind.		0.0531		0.0565		-0.413		-0.231
× Post-ACA		(0.0226)		(0.0221)		(0.201)		(0.170)
Age FE	N	N	Y	Y	N	N	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	1,067	1,067	1,067	1,067	1,064	1,064	1,064	1,064

Notes: Estimates of Equation 8, but with year fixed-effects in place of the post-ACA indicator. Standard errors clustered at the drug level.

Finally, we test the robustness of our results to allowing MMS to vary. In the core specification, we fix MMS to be the best pre-reform measure available. However, as discussed above, average MMS does grow over time and different drugs experience changes in MMS as well. Table A12 reports the results from allowing MMS to vary. We find even larger estimates for the impact of

Table A12: Estimates with Varying MMS

	Non-Med Discount		log(Non-Med Revenue)	
MMS	-0.567	-0.836	7.565	4.081
	(0.323)	(0.301)	(4.101)	(4.821)
Post ACA	0.0637	-0.0223	0.0953	0.0424
	(0.0161)	(0.0159)	(0.116)	(0.131)
MMS	0.227	0.334	-3.168	-1.697
× Post ACA	(0.142)	(0.146)	(1.372)	(1.462)
Age FE	N	Y	N	Y
Drug FE	Y	Y	Y	Y
N	1067	1067	1064	1064

the reform versus the baseline specification. This suggests that "mismeasuring" MMS can lead to attenuation in the post-reform slope, because firms are negotiating based on current MMS rather than 2009 MMS.

Alternative sample definitions

We also report robustness checks of our main results for different samples, and find qualitatively similar results. In both the FHM and KCC samples, the point estimates for non-Medicaid discount and non-Medicaid sales responses are qualitatively the same but slightly smaller in magnitude vs. our core sample (see Tables A13, A14, A15, and A16). The non-Medicaid discount response is statistically significant (or borderline significant) in both samples. The net non-Medicaid revenue response is statistically significant in the FHM sample but not the KCC sample.

Table A13: The Impact of the MDRP Change on Non-Medicaid Discounts (FHM Sample)

	Non-Medicaid Discount					
Post ACA	0.0665	0.0566	0.0586	-0.0111	-0.0208	-0.0187
	(0.00846)	(0.0112)	(0.00975)	(0.00984)	(0.0109)	(0.0102)
MMS		0.148			0.144	
× Post-ACA		(0.105)			(0.101)	
High MMS Ind.			0.0351			0.0335
× Post-ACA			(0.0191)			(0.0190)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1538	1538	1538	1538	1538	1538

Notes: Estimates of Equation 8. Standard errors clustered at the drug level.

Table A14: The Impact of the MDRP Change on Net Non-Medicaid Revenue (FHM Sample)

	log(Net Non-Medicaid Revenue)					
Post ACA	0.0400	0.180	0.117	-0.0632	0.0384	-0.0132
	(0.0600)	(0.0791)	(0.0615)	(0.0553)	(0.0791)	(0.0632)
MMS		-2.079			-1.522	
× Post-ACA		(1.040)			(0.909)	
High MMS Ind.			-0.345			-0.224
× Post-ACA			(0.169)			(0.148)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1535	1535	1535	1535	1535	1535

Notes: Estimates of Equation 8. Standard errors clustered at the drug level.

Table A15: The Impact of the MDRP Change on Non-Medicaid Discounts (KCC Sample)

	Non-Medicaid Discount					
Post ACA	0.0744	0.0592	0.0647	0.0308	0.0157	0.0206
	(0.0106)	(0.0144)	(0.0125)	(0.0139)	(0.0151)	(0.0144)
MMS		0.230			0.234	
× Post-ACA		(0.131)			(0.129)	
High MMS Ind.			0.0423			0.0473
× Post-ACA			(0.0219)			(0.0218)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1423	1423	1423	1423	1423	1423

Notes: Estimates of Equation 8. Standard errors clustered at the drug level.

Table A16: The Impact of the MDRP Change on Net Non-Medicaid Revenue (KCC)

	log(Net Non-Medicaid Revenue)					
Post ACA	-0.0948	-0.0275	-0.0527	-0.143	-0.114	-0.133
	(0.0717)	(0.0935)	(0.0797)	(0.0634)	(0.0855)	(0.0718)
MMS		-0.947			-0.419	
× Post-ACA		(0.966)			(0.865)	
High MMS Ind.			-0.175			-0.0451
× Post-ACA			(0.178)			(0.146)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1602	1602	1602	1602	1602	1602

Notes: Estimates of Equation 8. Standard errors clustered at the drug level.

Distribution of non-Medicaid discount variable

In addition, we report results relevant to the winsorization of the non-Medicaid discount variable. As noted in the main text, actual non-Medicaid discounts should fall between 0 and 1. However, due to reporting lags and other measurement issues, our non-Medicaid discount variable has negative values for some drug-years, a result of Medicaid net sales exceeding company-reported total net sales. In cases where total net sales is quite low, this can lead to very large negative outliers, some as small as -36, which in turn have a very large impact on our results. Figure A6 provides a box plot of the outcome variable. The way we deal with this in the core specification is by winsorizing the variable at the 5th and 95th percentiles. Another approach we try is to use the raw outcome but exclude outlier drugs with discounts of less than -1 in any given year. Table A17 contains the results of the exercise, which yield estimates that are similar and slightly larger in magnitude.

Table A17: The Impact of the MDRP Change on Non-Medicaid Discounts (Excluding Outliers)

	Non-Medicaid Discount					
Post ACA	0.0710	0.0482	0.0540	-0.00525	-0.0261	-0.0218
	(0.0125)	(0.0169)	(0.0150)	(0.0169)	(0.0177)	(0.0175)
MMS		0.317			0.288	
× Post-ACA		(0.147)			(0.136)	
High MMS Ind.			0.0642			0.0634
× Post-ACA			(0.0258)			(0.0254)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1036	1036	1036	1036	1036	1036

Notes: Estimates of Equation 8, using raw non-Medicaid discount data and excluding drugs with estimated discounts of less than -100% in any year. Standard errors clustered at the drug level.

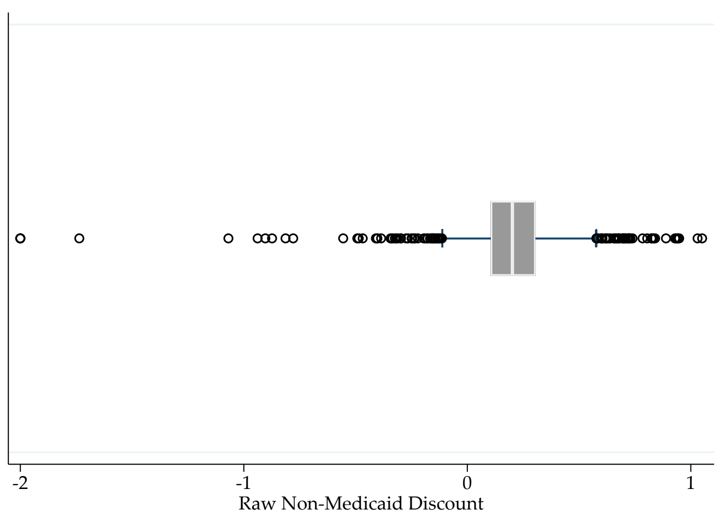


Figure A6: Box Plot of Non-Medicaid Discount Variable

Notes: A box plot of the raw non-Medicaid Discount variable, with whiskers covering the 5th and 95th percentiles. Outliers smaller than -2 are censored in the plot (-36.976, -7.44, -5.66, -2.04).

Full Results from Regression with Interacted Controls

We present full results corresponding to Panel A of Table 5 in the main paper. The goal is to provide clarity into whether some interacted controls are significant and suggestive of secular trends. In general, we find coefficients that are statistically insignificant and small in economic magnitude.

Table A18: Full Estimates from Table 5 of the Main Paper

	Non-Medicaid Discount					
	(1)	(2)	(3)	(4)	(5)	(6)
Post ACA	0.127	0.101	0.109	0.0573	0.0344	0.0397
	(0.0455)	(0.0471)	(0.0472)	(0.0580)	(0.0574)	(0.0576)
MMS		0.264			0.223	
× Post-ACA		(0.129)			(0.119)	
High MMS			0.0569			0.0538
× Post-ACA			(0.0224)			(0.0219)
2009 Non-Med Discount	-0.0480	-0.0379	-0.0508	-0.0225	-0.0134	-0.0232
× Post-ACA	(0.0690)	(0.0675)	(0.0691)	(0.0682)	(0.0666)	(0.0681)
log(2009 sales)	0.000713	-0.000367	-0.0000696	0.00258	0.00168	0.00201
× Post-ACA	(0.00635)	(0.00629)	(0.00628)	(0.00662)	(0.00654)	(0.00654)
log(2009 WAC)	0.00439	0.00237	0.00263	0.00463	0.00298	0.00297
× Post-ACA	(0.00751)	(0.00757)	(0.00772)	(0.00779)	(0.00781)	(0.00792)
2009 Age	-0.00987	-0.0102	-0.0105	-0.0215	-0.0211	-0.0217
× Post-ACA	(0.00683)	(0.00675)	(0.00674)	(0.0119)	(0.0117)	(0.0117)
2009 Age^2	0.000548	0.000551	0.000572	0.00174	0.00169	0.00173
× Post-ACA	(0.000347)	(0.000332)	(0.000336)	(0.000701)	(0.000685)	(0.000685)
Age FE	N	N	N	Y	Y	Y
Drug FE	Y	Y	Y	Y	Y	Y
N	1061	1061	1061	1061	1061	1061

Notes: Estimates of Equation 9 with non-Medicaid discount as the outcome. Age refers to the number of years a drug has been on the market.

MFCC Exposure Robustness Checks

Finally, Table A19 presents robustness checks related to Table 7 of the main text. Column 1 displays results with just one exposure group, defined as having a pre-ACA discount of greater than 15.1 percent. Columns 2 and 3 present results that shift the group definition range. As noted in the main text, the average non-Medicaid can be either larger or smaller than the highest discount referenced by Medicaid, depending on price dispersion and discounts in segments exempt from the Medicaid MFCC. Related to this, Column 4 presents estimates using data that incorporates the Medicaid rebate adjustment described in Online Appendix C.2. This adjustment also affects the group classifications. Relative to the core results in the main text, five drugs (mostly with high MMS) move from the low exposure group into the high exposure group. Finally, Column 5 presents estimates using data that is constructed under the assumption that AMP (the statutory price used by the Medicaid program) is 97 percent of WAC (the price measured in our raw data).

Generally, the results consistently show that the high exposure and low exposure groups have higher per-unit-MMS responses to the reform than the control group, albeit noisily so. The results also highlight the sensitivity of estimates to how the boundaries are defined. This problem results from the small number of data points in each group and the need to identify multiple differences in slopes to isolate heterogeneous per-unit-MMS responses. Therefore, the estimates are particularly sensitive to the movement of high MMS drugs across boundaries.

Table A19: Differences in Response by Exposure to MFCC (Adjusted Medicaid Rebate)

	Non-Medicaid Discount				
	(1)	(2)	(3)	(4)	(5)
MMS	0.0880	0.102	0.0909	0.0645	0.126
×Post ACA	(0.152)	(0.170)	(0.143)	(0.143)	(0.148)
Post ACA		-0.0648	-0.0288	-0.0423	-0.0258
×Low Exposure		(0.0316)	(0.0336)	(0.0274)	(0.0344)
MMS		0.266	0.326	0.460	0.316
×Post ACA×Low Exposure		(0.278)	(0.280)	(0.241)	(0.288)
Post ACA	-0.0672	-0.0857	-0.0915	-0.0848	-0.0937
×High Exposure	(0.0306)	(0.0407)	(0.0441)	(0.0399)	(0.0472)
MMS	0.321	0.161	0.439	0.336	0.458
×Post ACA×High Exposure	(0.254)	(0.351)	(0.418)	(0.305)	(0.454)
Fixed Effects	Drug, Year, Age				
Low Exposure Range	–	(0.211, 1]	(0.251, 1]	(0.231, 1]	(0.231, 1]
High Exposure Range	[0.151, 1]	[0.131, 0.211]	[0.171, 0.251]	[0.151, 0.231]	[0.151, 0.231]
Description	Two groups	Lower range	Higher range	MRC	AMP
N	1067	1067	1067	1067	1067

Notes: Estimates of Equation 11 of the main text with winsorized non-Medicaid discount as the outcome. Exposure Range refers to the drugs we classify as "High Exposure" and "Low Exposure," based on the 2009 non-Medicaid discount. $\beta_1 + \beta_5$ refers to the sum of the MMS-Post ACA coefficient and the MMS-Post ACA-High Exposure coefficient. MRC refers to the Medicaid correction discussed. This leads five drugs to move from the low exposure group to the high exposure group. AMP refers to results using data that assumes that AMP is 97 percent of WAC. Standard errors clustered at the drug level.

References

Centers for Medicare and Medicaid Services, "CMS Drug Spending, Historical Data," December 2016.

— , "State Drug Utilization Data," January 2019.

Dranove, David, Christopher Ody, and Amanda Starc, "A Dose of Managed Care: Controlling Drug Spending in Medicaid," 2017.

Duggan, Mark and Fiona. M. Scott Morton, "The Distortionary Effects of Government Procurement: Evidence From Medicaid Prescription Drug Purchasing," *Quarterly Journal of Economics*, 2006, *121* (1), 1–30.

Kakani, Pragya, Michael Chernew, and Amitabh Chandra, "Rebates in the Pharmaceutical Industry: Evidence from Medicines Sold in Retail Pharmacies in the U.S.," 2020.

Kury, Fabricio S.P., "Mapping U.S. FDA National Drug Codes (NDC) to Drug Classes and Codes," September 2020.

SSR Health, "SSR Health Brand Rx Net Pricing Tool, 2019Q1," August 2019.

U.S. Bureau of Labor Statistics, "Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL]," November 2021.