A Methodology for Estimating Medicaid and Non-Medicaid Net Prices Using Top Brand-Name Drugs, 2015–2019

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This methodological brief outlines the techniques developed for a cross-sectional study of the 18 most popular brand-name drugs (Clemans-Cope et al. 2023). That study aimed to address the issue of high prices and spending on brand-name prescription medications in the United States. The list price of brand-name drugs is usually much higher than the "net" price paid for them in the three major prescription drug insurance markets: commercial, Medicare Part D, and Medicaid. Data on list prices are more generally available but information on net prices is proprietary, making it difficult for researchers and policymakers to gain an accurate estimate of how net prices and net spending have grown over time.

A key dataset used by policy researchers, SSR Health, makes rebate information available in their US Brand Rx Net Pricing Tool. SSR Health has published quarterly data since 2007 that contain rebates averaged across all payers and apportioned between Medicaid and non-Medicaid payers. However, the estimated Medicaid rebate does not account for the Medicaid best price provision.[1] "Best price" is the lowest price available to wholesalers or retailers in the commercial sector and is incorporated into Medicaid's basic rebate. For certain brand-name drugs, this rule can have a large effect on Medicaid's net price.

Unlike drug prices in the commercial and Medicare Part D markets, which are set through negotiations between manufacturers and payers, Medicaid drug prices are set by precise rules embedded in legislation passed by Congress. We use the rules that define Medicaid's prices along with

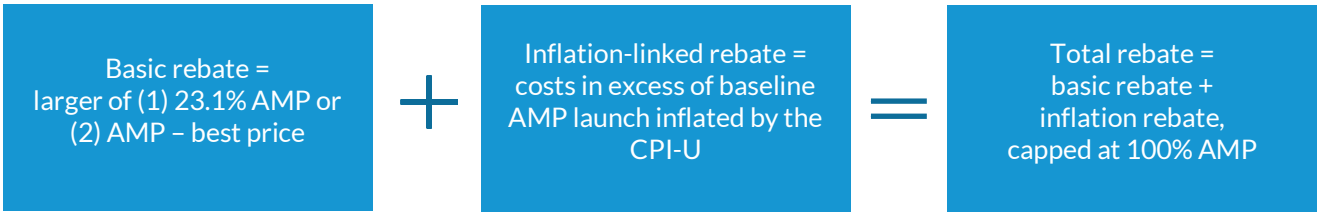
additional data sources to present a method for more accurately estimating Medicaid net prices. We incorporate the basic rebate, including our estimate of the best price provision and the inflation-linked rebate, in conjunction with a separate study of top-selling drugs from 2015 to 2019 (Dickson 2019). We then separate Medicaid's net prices, which are roughly 20 percent of the overall market, from non-Medicaid net prices in the SSR Health data to offer more accurate analysis of net drug prices and trends for policymakers.

Background on the Medicaid Rebate

The Medicaid rebate consists of two components referred to as the *basic rebate* and the *inflation-linked rebate*. For brand-name drugs, the basic rebate is the larger of 23.1 percent of the average manufacturer price (AMP) or the difference between the AMP and the best price. Best price is the lowest available price to any wholesaler, retailer, or provider in the commercial sector. This excludes prices offered to certain government programs such as the US Department of Veterans Affairs (VA). In addition to the basic rebate, there is an inflation-linked rebate, which is calculated as the difference between the drug's current-quarter AMP and its baseline AMP from the drug's launch date inflated by the CPI-U (i.e., the Consumer Price Index for All Urban Consumers). The total rebate, consisting of the basic rebate plus the inflation-linked rebate, is capped at 100 percent of AMP during the time of our study. If not capped, it could exceed this limit (figure 1).

FIGURE 1

Calculation of Medicaid Rebates for Brand-Name Drugs, 2015–19



Source: Authors' methodology.

AMP = average manufacturer price; CPI-U = Consumer Price Index for All Urban Consumers.

Data Sources, Definition of the Sample, and Standardization of the Data

To develop and apply our methodology, we used Medicaid State Drug Utilization Data (Medicaid SDUD) from 2015 through 2019 published by the Centers for Medicaid and Medicare Services (CMS) to proxy Medicaid total sales, including both fee-for-service and managed care programs. We used Medicaid Drug Rebate Program data published by CMS to identify launch dates to estimate Medicaid's manufacturer rebate provisions. We used SSR Health data to estimate wholesale acquisition cost (WAC) unit prices, WAC launch prices, total net sales, WAC-to-net-discount ratios, and total sales at WAC. We also used Medi-Span to estimate WAC unit prices and WAC launch prices missing from SSR Health.

To estimate Medicaid's best price provision, we used Federal Supply Schedule (FSS) prices published by the VA. We used the FSS price available to all direct federal purchasers and the "Big Four" price available to the VA, the US Department of Defense, the Public Health Service, and the Coast Guard. We estimated the FSS price per unit using the number of units per package drawn from Medi-Span. Data were accessed and analyzed between January 2019 and June 2021.

For clarity, table 1 presents our price measures and definitions, drawing on and updating a similar table published in a Congressional Budget Office (CBO) report (CBO 2005).

TABLE 1

Price Measures, Descriptions, Data Sources, and Availability of Prescription Drugs Studied for Analysis of Data, 2015–19

Price	Description	Details	Data sources and availability
Wholesale acquisition cost (WAC)	Manufacturer's list price to wholesalers	This is the published list price, though in practice the WAC is not the wholesaler's price; WAC is thought to be slightly higher than what retail pharmacies pay (Seeley 2022).	SSR Health and Medi-Span data. Both can be purchased.
Average manufacturer price (AMP)	Average price that retail purchasers pay manufacturers	This is the price before rebates or discounts; a 2021 report found that AMP was 91% of WAC and 98% of the Medicaid retail price (CBO 2021).	Estimated from SSR Health and Medi-Span.
Nonfederal average manufacturer price (non-FAMP)	Average price that retail and nonretail nonfederal purchasers pay manufacturers	This price includes discounts; a 2021 report found that non-FAMP was 90% of AMP and 82% of WAC (CBO 2021).	Estimated as 82% of WAC from SSR Health.
Best price (BP)	Lowest available price to wholesalers or retailers in the private sector	This price excludes government programs like the 340B drug pricing program and Veterans Affairs (VA); however, BP is used in computing the Medicaid rebate (Dolan and Tian 2020). Note that BP could be lower than Federal Supply Schedule (FSS) because the set of purchasers used for FSS could exclude the BP purchaser.	Not publicly available. In this study, we estimate BP using a method based on FSS prices.
Federal Supply Schedule (FSS) price	Price negotiated by the VA and available to government agencies other than the Big Four (i.e., not the VA, the Department of Defense, the Public Health Service, including the Indian Health Service, and the Coast Guard)	This price is determined by statutory rules and negotiation by the VA with manufacturers; it cannot increase faster than inflation or the net price charged to the most favored customer during the contract period (CBO 2021). Often based on most favored customer price. Usually higher than the Big Four price, although a single FSS price can be offered to the Big Four and other government agencies.	Publicly available in the FSS data file.

Price	Description	Details	Data sources and availability
Big Four price	Price negotiated by the VA and available to the Big Four (the VA, the Department of Defense, the Public Health Service, including Indian Health Service, and the Coast Guard)	The Big Four price is the minimum of the FSS price and the FCP, minus any additional price concessions (CBO 2021), and must be no higher than the FCP or the FSS max cap.	Publicly available in the FSS data file.
Most favored customer (MFC) price	The lowest price paid by a private purchaser, including discounts	Used in negotiations with VA to establish the FSS price, MFC is a private market price that represents purchasers on similar terms and conditions getting the best deals. Conceptually, the MFC is to the VA what the BP is to Medicaid.	Not publicly available; it is used conceptually in this study.
Federal ceiling price (FCP)	Upper limit on price charged to Big Four agencies.	In the first year of contract period, the FCP is 24% off (i.e., 76% of) the prior year's non-FAMP (CBO 2005).	Estimated as 76% of 82% of the previous year's WAC.
FSS max cap	FSS price offered to other government agencies sets the FSS max cap (Anderson, Ruscus, and Lewis 2017)	The FSS max cap caps the FCP in the second and subsequent years of a contract.	We do not estimate this measure; it is used conceptually.

Source: Authors' summary based on Congressional Budget Office, "Prices for Brand-Name Drugs under Selected Federal Programs" (Washington, DC: CBO, 2005).

Adjusting Estimates for Inflation

All estimates of drug spending are expressed in nominal terms, unadjusted for general inflation. Because new drugs and new formulations were introduced during the period of our study, however, our simple average of prices across drugs over time is subject to distortion from high-cost drugs with low volume. To address this issue, we weighted all estimates of Medicaid and non-Medicaid gross and net spending, prices, and rebates by average gross Medicaid spending by national drug code (NDC) at the NDC-11 level during 2015–19, which identifies manufacturer, drug, and package information.

Identifying a Sample

In exploratory analysis of pricing relationships, we first identified a sample of the top-selling Medicaid and Medicare drugs. We selected the top 100 products by spending in 2015 and 2018 from Medicaid and Medicare Part D data, resulting in an initial sample of 222 products. Medicaid SDUD is produced at the NDC level (i.e., product, strength, and package size level), so we created an NDC-to-product crosswalk using data from SSR Health and the National Drug Code Directory from the FDA. Medicare Part D product names are inconsistent with the SSR Health and FDA crosswalk, so duplicate products were identified and collapsed manually. This resulted in an initial sample of 194 products. We dropped 37 generic products, resulting in a sample of 157 products. However, only 156 products and 995 NDCs appear in the 2015 and 2018 Medicaid SDUD; thus, the final exploratory sample contained 156 products, corresponding to 2,580 NDCs.

For our final estimates we incorporated publicly available data from IQVIA on top-selling drugs in 2015–19 by gross spending, as IQVIA provides the most complete data on gross spending (IQVIA 2020). This step required us to limit our final analysis to the 18 top-selling drugs as measured by IQVIA's marketwide data. The product mix in Medicaid is different from that of non-Medicaid. As a result, from IQVIA's publicly available marketwide data on the 20 top drugs by nondiscounted spending (that is, spending not adjusted for discounts and rebates), we identified 18 drugs with definitions corresponding to SSR Health. We excluded two drugs (Lantus SoloStar and Victoza 3-Pak) for which the included formulations differed substantially from the top-selling drugs identified in our larger exploratory sample (table 2). These 18 drugs were associated with 68 NDC-9 codes, combined across package sizes, in the 2015–19 Medicaid utilization data.

Cleaning Unit Data

Unit and route data for each NDC are necessary to calculate the Medicaid rebate, which is calculated per unit (e.g., milliliter, gram, or "each," such as a pill or tablet) and informed by route (e.g., oral solid, implanted, inhaled, injected, instilled, transdermal patch, kit). For example, a kit uses the "each" unit, wherein one unit is equal to one kit, and an oral solid uses the "each" unit, wherein one unit is equal to one pill. We filled in missing unit and route information for all NDCs manually by examining packaging information.

TABLE 2

Estimated Medicaid Gross Spending and Medicaid average Gross Price, Savings Attributable to Best Price and Inflationary Rebates, and Net Price Discount per 30-Day Supply for 18 Top-Selling Brand-Name Drugs, Weighted by Average Gross Medicaid Spending, 2015 and 2019

		Medicaid gross spending ($m)		Medicaid average gross price per 30-day supply ($)[a]		Medicaid average savings from inflationary rebate per 30-day supply ($)		Medicaid average savings from best price provision per 30-day supply ($)		Medicaid average rebate discount (% of gross price per 30-day supply)	
Brand name	**Generic name(s)**	**2015**	**2019**	**2015**	**2019**	**2015**	**2019**	**2015**	**2019**	**2015**	**2019**
Total or Total average		**3,620.5**	**9,894.0**	**2,631**	**3,667**	**838**	**1,566**	**46**	**106**	**62**	**70**
Biktarvy	bictegravir, emtricitabine, and tenofovir alafenamide	n.d.	1,040.7	n.d.	2,785	n.d.	24	n.d.	0	n.d.	24
Eliquis	Apixaban	31.1	366.9	332	458	66	172	56	246	60	100
Enbrel	etanercept	446.1	555.5	3,046	4,905	1,656	3,297	0	1	77	90
Genvoya	elvitegravir, cobicistat, emtricitabine, and tenofovir alafenamide	1.6	792.9	2,346	2,785	0	276	0	0	23	33
Humira	adalimumab	810.4	2,222.1	3,218	5,196	1,761	3,055	0	0	78	82
Ibrance	palbociclib	42.8	302.3	8,968	10,773	0	1,056	0	0	23	33
Januvia	sitagliptin	336.2	553.0	393	530	193	315	1	0	72	83
Jardiance	empagliflozin	8.8	255.3	372	533	48	186	27	36	43	65
Keytruda	pembrolizumab	1.9	257.4	2,791	3,074	0	50	0	0	23	25
Opdivo	nivolumab	7.9	168.0	10,512	11,706	58	373	0	0	24	26
Remicade	infliximab	181.6	185.2	1,006	1,196	324	463	44	25	60	64
Rituxan	rituximab	116.6	145.6	2,209	2,807	806	1,301	0	0	60	69
Stelara	ustekinumab	85.7	474.9	12,436	16,863	4,532	8,426	997	2,687	67	89
Symbicort	budesonide/formoterol	456.8	609.7	256	323	101	157	52	2	83	72

Brand name	Generic name(s)	Medicaid gross spending ($m)		Medicaid average gross price per 30-day supply ($)[a]		Medicaid average savings from inflationary rebate per 30-day supply ($)		Medicaid average savings from best price provision per 30-day supply ($)		Medicaid average rebate discount (% of gross price per 30-day supply)	
		2015	2019	2015	2019	2015	2019	2015	2019	2015	2019
Tecfidera	dimethyl fumerate	219.7	313.7	5,128	7,240	819	2,608	0	0	39	59
Trulicity	dulaglutide	3.8	333.2	557	787	48	243	0	0	32	54
Vyvanse	lisdexamfetamine dimesylate	749.7	973.6	182	250	76	133	0	5	69	80
Xarelto	rivaroxaban	119.8	344.1	321	451	95	202	0	0	52	68

Sources: Medicaid State Drug Utilization Data, Federal Supply Schedule Data, SSR Health, and IQVIA total spending.

Notes: All spending, prices and rebates are weighted by average quarterly gross Medicaid spending at the NDC-11 level in the five-year period to compute annual estimates by drug. Drugs are aggregated to an annual index, weighting by average gross Medicaid spending in the five-year period. Prices were standardized to a 30-day supply by product in cases in which the prescription exceeded 30 days.

n.d. = no data. Biktarvy was launched in 2018.

[a] Medicaid gross price is estimated average manufacturer price.

Standardizing Quantities for the Cost of a 30-Day Supply

For comparing the costs of drugs, we standardized quantities by estimating the cost of a standard 30-day supply. We first used the defined daily dose per product, published by the World Health Organization.[2] We then multiplied the defined daily dose by 30 to obtain the recommended 30-day dose. Four products did not have published defined daily doses (Ibrance, Keytruda, Opdivo, and Rituxan); for these, we determined the recommended 30-day dose on the basis of general product guidelines.[3] We then determined the active ingredient amount, generally in milligrams, per package size (NDC-11). This amount was often published in the Medicaid Drug Rebate Program dataset and was also hand-checked for every NDC-11 in our sample. For each NDC-11, we created a factor equal to the 30-day dose divided by the total active milligrams in the package. For three products (Biktarvy, Genvoya, and Ibrance), the 30-day dose was based on the number of tablets and we created a factor equal to the recommended number of tablets in a 30-day supply. For one product (Symbicort), the 30-day dose was based on the number of inhales; for this product, we created a factor equal to the 30-day recommended number of inhales divided by the number of inhales in the package.

We calculated the net unit price per NDC-11 by subtracting the unit rebate amount, calculated across package sizes, from AMP. We then calculated the net price per package by NDC-11 by multiplying the net price per unit by the number of units in the package, which was obtained from Medi-Span data. We calculated the price per 30-day supply by multiplying the net price per package by the previously described factor. We follow the same steps to calculate a WAC price per 30-day supply, starting with the WAC unit price per NDC-11 rather than the estimated net price.

Method of Estimating Medicaid Manufacturer Drug Rebates

Estimating Average Manufacturer Price

Medicaid drug rebates are calculated from several components, including AMP, the average price paid to the manufacturer in the United States by retail pharmacies and the wholesalers who distribute to them. AMP is not available to the public, but the CBO has found it to be approximately 91 percent of WAC (CBO 2021). For our analysis, we extracted WAC at the NDC-9 level, which specifies the product-strength dosage but combines across package sizes, from SSR Health data. We then used Medi-Span data to fill in gaps (1 percent of 1,090 NDC-9 quarters).

Comparing Medi-Span Data

To validate the WAC data in SSR Health, we compared those prices to prices reported in Medi-Span data at the product-strength level for the top five products by spending in 2018. Those products were Humira, Invega Sustenna/Trinza, Latuda, Mavyret, and Vyvanse. We compared Medi-Span and SSR data for 230 unique product-strength quarters in 2015 and 2018 and found that 93 percent of reported

prices were within 1 percent of each other, with the remaining 7 percent varying by between 1 percent and 6 percent. These small differences can occur from variation in the time that the price was recorded. Thus, we conclude that the SSR Health WAC data were reliable.

Estimating Medicaid's Best Price

The key contribution of our research is developing and testing a methodology for estimating Medicaid's best price provision, a critical step in estimating Medicaid's overall drug rebates. Because best price is not publicly available, we use the FSS price as a surrogate for the best price.

In the first step of estimating Medicaid's best price provision, our method uses the relationships between FSS price, federal ceiling price (FCP), and Big Four price, which are publicly available and defined or limited by federal statute, to identify when the FSS price is a good estimate of the best price. We perform this analysis at the NDC-9 level for each quarter in our study period.

The FSS price is based on the price that manufacturers charge their most favored commercial customer (MFC). On average, MSC is lower than best price because it may include additional discounts for federal customers such as the VA (CBO 2005). The FCP is the maximum price that manufacturers can charge the Big Four for brand-name drugs and is equal to 76 percent of the nonfederal AMP (non-FAMP) from the previous fiscal year, plus additional discounts when the non-FAMP rises faster than inflation.

The Big Four price is offered to the VA, the US Department of Defense, the Public Health Service, and the Coast Guard. It cannot exceed the FCP and is often less, as it includes additional voluntary discounts provided to the Big Four agencies plus additional discounts when the non-FAMP rises faster than inflation (CBO 2021).

To accurately interpret the prices published in the FSS, it is useful to understand whether manufacturers offer single or dual pricing. "Single pricers" voluntarily choose to provide federal purchasers with a price capped at the FCP. This option may be administratively less burdensome. These manufacturers maintain a single price list and are identified in the FSS data by the fact they publish only one price: an FSS price. "Dual pricers" establish two price lists: one FSS price and a second Big Four price. Manufacturers make this election for all drugs at the time of the contract award. Single pricers can choose to change to dual pricing at any time during the contract period, but this decision affects all drugs under that manufacturer. Dual pricers can choose to offer all FSS purchasers the lower Big Four price for a period through a temporary price reduction without changing their election from dual to single pricing (Anderson, Ruscus, and Lewis 2017).

When the published FSS price is greater than the Big Four price, we assume that the FSS is a good estimate of best price: the higher FSS price is most likely based on the MFC discount, whereas the Big Four price is capped at the FCP discount and the manufacturer is acting as a dual pricer. This accounts for 69 percent and 56 percent of NDC-11s in our larger sample of drugs in 2015 and 2018, respectively (weighted by raw Medicaid sales), and 51 percent of NDC-11s in our sample of 18 top drugs from 2015 to 2019.

When the FSS price equals the Big Four price and both are equal to or higher than FSS price in the previous quarter, we assume that the increase in FSS price reflects an increase in the FCP, and FSS is a good estimate of best price. In this case, the manufacturer is most likely a dual pricer but has offered all federal purchasers the same price as the Big Four. This situation accounts for 11 percent and 29 percent of NDC-11s in our larger sample in 2015 and 2018, weighted by raw Medicaid sales, and 25 percent of NDCs in our sample of 18 top drugs from 2015 to 2019.

When only an FSS price and no Big Four price is published, we assume the single price is based on the FCP for all FSS purchasers. In this situation, we still use the FSS price to approximate best price. Although this may overestimate the best price provision, failing to use the FSS price would underestimate the best price provision. In this case, we know that the manufacturer is acting as a single pricer. This situation accounts for 18 percent and 14 percent of NDC-11s in our larger sample in 2015 and 2018, weighted by raw Medicaid sales, and 22 percent of NDCs in our sample of 18 top drugs from 2015 to 2019. We do not have FSS data for 2 percent and 1 percent of NDCs in 2015 and 2018 in the larger sample and 0.2 percent of NDCs in our sample of top 18 products, weighted by Medicaid sales. For these NDCs, we do not compute a best price estimate.

FSS data are published to the public biweekly. We use additional information derived from Medi-Span data to obtain the number of units per NDC to estimate the FSS price per unit.44 We use the file published on the 15th from the first month of each quarter (January, April, July, and October). This file appears to be more consistent than the files published on the first of the month. FSS files often contain prices for multiple contract periods for the same drug in the same file; we use only the records from the latest contract period. The file contains duplicate records by NDC-11 and price type, but 98.8 percent of the duplicate records list the same price. When different prices are listed for the same NDC quarter, we use the average of the prices (table 3).

TABLE 3

Federal Supply Schedule and Big Four Price Relationship by National Drug Code in 2015 and 2018

	Is FSS price a good indicator of best price?	Percent Distribution			
		Larger sample		IQVIA sample	
		2015	2018	2015	2018
FSS price is larger than Big Four price	Yes	69	56	47	39
FSS price is equal to Big Four price	Yes, when both are higher than or equal to the previous quarter's FSS price	11	29	10	44
FSS price only	Will overestimate best price provision, but not using it will underestimate	18	14	43	17
No published FSS price	Not available	2	1	0	0

Source: Authors' calculations.

Notes: Percentages are weighted by raw Medicaid sales. When FSS price is equal to Big Four price, FSS price is a good indicator of best price when both are higher than or equal to the previous quarter's FSS price. This occurs for 63 percent of NDCs in 2015 and for 79 percent of NDCs in 2018 in the larger sample and for 9 percent of NDCs in 2015 and 39 percent of NDCs in 2018 for the IQVIA sample.

Smoothing FSS Prices over Contract Periods

In the second step of estimating Medicaid's best price provision, we smooth the FSS published prices over time to account for discontinuities resulting from five-year contract periods. Because FSS prices cannot generally increase faster than inflation during a contract period (Anderson, Ruscus, and Lewis 2017), large price discontinuities are often observed every five years at the start of a new contract. Use of the actual FSS to proxy best price in the quarters just before the FSS contract date would underestimate the true best price and thus overestimate the best price discount.

We smooth the FSS prices at the NDC-11 level according to the following rules:

1. In the four quarters following a new contract, we use the published FSS price, as prices are renegotiated at the start of each contract. We also use the published price from the earliest published FSS price, using data beginning in 2008.
2. When there are two or more new contracts, we average quarterly prices in the first four quarters of each contract and apply the average rate of growth in the intervening quarters.

The first two rules account for 12 percent and 34 percent, respectively, of the NDCs in our sample of 1,901 NDC-11s for the top 18 drugs in 2015–19 and for 10 percent and 31 percent, respectively, of the NDCs in our larger exploratory sample of 6,689 NDC-11s in 2015 and 2018, weighed by raw Medicaid spending.

For the remaining number of NDCs not handled with rules 1 and 2, we defined two additional rules:

3. We use the average quarterly percent growth in FSS price for all other NDCs within a product. (This adjustment was used for less than 1 percent of NDCs in our broader sample and not used at all in our smaller sample.)
4. For quarters before the first contract date, we calculate the average FSS to WAC ratio for the first four quarters of the new contract and apply this ratio to quarters before the first contract year, and we take the same approach for quarters after the last contract date.[5]

We then aggregate across package sizes to the NDC-9 level, using the lowest smoothed FSS price among package sizes for the NDC-9 group. We then choose the larger of the published FSS price or the smoothed price per NDC-9. We are assuming an increase in the FSS price from one contract to another reflects a real price increase in the price offered to the MFC.

Computing the Total Medicaid Rebate

The third step in our methodology is to apply our best price estimate to the formula for determining Medicaid's basic rebate (table 4). We then compute the inflation-linked rebate to calculate the total Medicaid rebate. Though SSR Health computes the Medicaid rebate at the product-strength level, we choose to compute it at the NDC-9 level, combining across package sizes, consistent with CMS and CBO. We calculate the basic rebate for brand-name drugs at the NDC-9 level (across package sizes) in

each quarter as the greater of (1) 23.1 percent of estimated AMP or (2) estimated AMP minus our best price estimate.[6] We define the best price at the NDC-9 level by selecting the lowest estimate of best price among the NDC-11 records.

We estimate AMP as the average AMP within the NDC-9 group, weighting each NDC-11 record by raw Medicaid sales. We use the earliest launch quarter within the NDC-9 group, identifying launch quarter by NDC-11 from the Medicaid Drug Rebate Program data. We estimate baseline AMP as 91 percent of the WAC from the earliest launch quarter within the NDC-9, using WAC prices listed in SSR Health or Medi-Span data to fill data gaps, which accounted for about half of NDCs.

To compute Medicaid's inflation-linked rebate, we estimated baseline AMP as 91 percent of the WAC from the earliest launch quarter within the NDC-9 (CBO 2021). We use the launch quarter listed in the Medicaid Drug Rebate Program data and the baseline AMP from WAC prices listed in SSR Health or Medi-Span data to fill data gaps, which account for about half of NDCs. We compute the allowable growth caused by inflation by multiplying the estimated baseline AMP by an inflation factor representing growth from the baseline quarter to the present quarter using the CPI-U, as

baseline AMP × (quarterly CPI-U / baseline CPI-U)

If estimated quarterly AMP is greater than allowable inflation growth, we subtract the allowable growth from the quarterly AMP to determine the inflation-linked rebate. If the quarterly AMP is less than or equal to the allowable inflation growth, the inflation-linked rebate is set to zero.

To estimate Medicaid rebate amounts for each drug, we compute the unit rebate from both the basic rebate and the inflation-linked rebate as a percentage of AMP at the NDC-9 level and apply that to total Medicaid spending.

TABLE 4

Sources and Calculations Used to Compute Medicaid and Non-Medicaid Prices

	Data point	Source or calculation
Gross spending		
1	Total gross spending	IQVIA
2	Medicaid gross spending	CMS
3	Non-Medicaid gross spending	= total gross spending (1) – Medicaid gross spending (2)
Rebates		
4	Total net spending	SSR
5	Total rebate percent	SSR
6	Medicaid rebates	Estimated, as described in methods
7	Non-Medicaid rebates	= total gross spending (1) – total net spending (4) – Medicaid rebates (6)
WAC spending		
8	Total WAC spending	= total net spending (4) × (1 ÷ total rebate percent (5))
9	Medicaid's share of gross spending	= Medicaid gross spending (2) ÷ Total gross spending (1)
10	Medicaid WAC spending	= total WAC spending (8) × Medicaid's share of gross spending (9)
11	Non-Medicaid WAC spending	= Total WAC spending (8) – Medicaid WAC spending (10)

	Data point	Source or calculation
Net spending		
12	Medicaid net spending	= Medicaid gross spending (2) — Medicaid rebates (6)
13	Non-Medicaid net spending	= Non-Medicaid gross spending (3) — Non-Medicaid rebates (7)
Prices		
14	Medicaid net to WAC spending ratio	= Medicaid net spending (12) ÷ Medicaid WAC spending (10)
15	Non-Medicaid net to WAC spending ratio	= Non-Medicaid net spending (13) ÷ Non-Medicaid WAC spending (11)
16	Medicaid price	= Medicaid net to WAC spending ratio (14) × WAC price
17	Non-Medicaid price	= Non-Medicaid net to WAC spending ratio (15) × WAC price

Source: Authors' methodology.
Note: All calculations are by product.

Net Medicaid and Non-Medicaid Spending on Top-Selling Brand-Name Drugs

Estimating net aggregate Medicaid spending would be straightforward if consistent unit data were available. Because data are inconsistent, we combine information from three sources. We use three estimates of spending: (1) spending at WAC prices, which represent the manufacturers' prices to wholesalers before any discounts or rebates; (2) gross spending, or actual spending by payers and patients before rebates; and (3) net spending, or spending after rebates. IQVIA publishes total gross spending, Medicaid SDUD publishes Medicaid gross spending, and SSR Health publishes total net spending.

To estimate spending at WAC prices, we first multiply total net sales by the total WAC-to-net discount, both at the product level from SSR Health data, to estimate total sales at WAC prices by product. Medicaid sales at WAC as a share of total sales at WAC are proxied by estimating a similar ratio, Medicaid's share of retail spending, by dividing Medicaid spending from SDUD by total retail sales from IQVIA, which is 12.7 percent, weighted by Medicaid retail spending. We apply this share to spending at WAC to approximate Medicaid and non-Medicaid spending at WAC. Using this approach, we likely underestimate Medicaid sales at WAC because Medicaid retail prices are lower than Medicare Part D retail prices (CBO 2021) and are likely lower than non-Medicaid retail prices, leading to a lower Medicaid share at retail versus WAC prices.

We then compute Medicaid total net spending (Medicaid retail spending from SDUD minus estimated Medicaid rebates) and non-Medicaid total net spending (non-Medicaid total retail sales minus non-Medicaid rebates), where non-Medicaid retail sales is IQVIA total retail sales minus Medicaid total sales from SDUD and the non-Medicaid rebate is IQVIA retail sales minus SSR net sales minus total estimated Medicaid rebates. We use these to compute Medicaid and non-Medicaid net spending to total WAC spending ratios.

Last, to estimate Medicaid and non-Medicaid net unit price and net 30-day price, we apply these ratios to the WAC unit price and WAC 30-day price from Medi-Span, where the WAC unit and 30-day prices are averaged by product, weighting by raw Medicaid sales. Because the Medicaid net spending-to-WAC sales ratio is an overestimate, this may result in a Medicaid price that is slightly too high.

To measure the price growth of brand-name specialty drugs between 2015 and 2019, we examine each drug separately in Medicaid and non-Medicaid sales, as well as the overall change in net price of a drug over time; this approach captures changes in the prices of individual drugs as well as shifts in the mix of drugs used between years. This approach might create a higher estimate of price growth because it incorporates not only the growth captured by the price-index approach but also the shift in use toward higher-priced drugs during the period examined.

Conclusion

By incorporating our method for estimating Medicaid's best price provision into the total rebate calculation, we increase the accuracy of estimates of Medicaid prescription drug price discounts. As a result, we can also improve the estimates of Medicaid and non-Medicaid net prices, net spending, and trends in price growth over time. Adding the best price provision increases the size of the Medicaid rebate and thus reduces estimates of net spending by Medicaid. Reducing the estimates of net Medicaid spending increases estimates of net spending by non-Medicaid sources of coverage (including commercial and Medicare Part D insurers) when applied to aggregate data from SSR Health, a data source commonly used by researchers. Incorporating the best price provision into Medicaid rebate calculations thus improves the estimates of net prices paid by commercial and Medicare Part D plans, which are currently at the center of various proposed drug pricing reforms.

In results published elsewhere (Clemans-Cope et al. 2023), we find that the best price rebate reduced the net prices of about one-third of the top-selling 18 brand-name drugs we examined. While the inflation-linked rebate accounted for a much larger share of the Medicaid rebate compared with the best price rebate, the best price rebate was meaningful for several drugs. Rigorous and transparent methods for estimating Medicaid discounts are critical for understanding patterns in prices and spending for developing strategies to restrain drug price growth in a way that better aligns drug price with clinical benefits.

Notes

[1] Benedic Ippolito and Joseph Levy, "Best Practices Using SSR Health Net Drug Pricing Data," *Health Affairs Forefront* (blog), March 10, 2022, https://www.healthaffairs.org/do/10.1377/forefront.20220308.712815/.

[2] "The ATC/DD Toolkit: Defined Daily Dose (DDD)," World Health Organization, 2021, https://www.who.int/tools/atc-ddd-toolkit/about-ddd.

[3] We used the following recommended 30-day doses for products without a published defined daily dose: Ibranace 30-day supply = 21 units; Keytruda 30-day supply = 71 mg, based on the recommended 100 mg per 6 weeks; Opdivo 30-day supply = 480 mg; and Rituxan 30-day supply = 330 mg, based on the recommended 2 g per 6 months.

[4] We thank Erik Pachman of 46Brooklyn.com for merging Medi-Span and FSS data files to generate FSS price per unit.

[5] The smoothing algorithm substantially reduces the impact of our estimates of the best price provision in Medicaid. In a broader sample of drugs than used for this study, we found that 41 percent of NDC-9-quarters weighted by sales to Medicaid in 2015 and 58 percent in 2018 triggered the best price provision in the basic rebate calculation without using a smoothed FSS price. After smoothing, only 28 percent of NDC-9-quarters weighted by sales to Medicaid in 2015 and 24 percent in 2018 triggered the best price provision.

[6] We compute the Medicaid rebate at the NDC-9 level, combining across package sizes. We estimate AMP as the average AMP within the NDC-9 group, weighting by raw Medicaid sales. We estimate best price as the lowest smoothed FSS price per unit among package sizes in the NDC-9 group. We use the earliest launch quarter in the NDC-9 group (across package sizes), identifying launch quarter by NDC-11 from the Medicaid Drug Rebate Program data. We estimate baseline AMP as 91 percent of the WAC from the earliest launch quarter within the NDC-9, using WAC prices listed in SSR Health or Medi-Span data to fill data gaps, which account for about half of NDCs.

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