# Plan-Level Formulary Variation in Medicaid Managed Care


## Abstract

States differ in whether Medicaid managed care plans must follow a common preferred drug list or may publish plan-specific formularies. We assembled current public Medicaid managed care formulary and preferred-drug-list sources collected through May 20, 2026, and linked them to the top 100 Medicaid drugs ranked by 2024 State Drug Utilization Data gross spend. The current source universe contains 103 plan/source rows across 19 states, including 74 plan rows in states without a binding common preferred drug list. In that no-common-PDL sample, 56.0 percent of plan-drug cells were not listed or unmatched, 21.8 percent were preferred with utilization management, 7.8 percent were nonpreferred, 7.6 percent were preferred without utilization management, and 6.8 percent had mixed within-plan matches. Within-state exact-status agreement was low in several states, and high-spend drugs such as Dupixent, Ozempic, Trulicity, Symbicort, and Eliquis repeatedly varied across plans. These findings suggest that plan choice in Medicaid managed care can also be a pharmacy-access choice.


## Introduction

Medicaid pharmacy policy is usually described at the state level, but many beneficiaries experience it through managed care plan choice. A state may require all plans to follow one preferred drug list (PDL), carve pharmacy benefits out of managed care, or allow plans and their pharmacy benefit administrators to publish distinct formularies. Those governance choices matter because a beneficiary, prescriber, or enrollment counselor may reasonably assume that Medicaid plans in the same state cover high-cost drugs in the same way when public plan documents say otherwise.

The policy question is timely. State Medicaid agencies face growing pressure to manage prescription drug spending while preserving access to clinically important therapies. Federal and state oversight of managed care has also become more explicit about access, transparency, and quality. Yet a basic descriptive question remains undermeasured: after removing states with a binding common PDL, how much plan-level formulary variation remains in Medicaid managed care?

Prior research shows that Medicaid managed care coverage and utilization-management rules can vary for medications for opioid use disorder, alcohol use disorder medications, opioid prescribing, and pediatric behavioral health medications.1-5 Broader formulary variation has also been documented in Medicare Part D.6 The contribution here is different. We build a source-backed national Medicaid managed care formulary panel across therapeutic areas, first separating common-PDL states from states where plan-level comparison is meaningful, then measuring variation for high-spend drugs.

## Data And Methods

We constructed a state and plan source universe for mainstream comprehensive Medicaid managed care plans where outpatient pharmacy formulary comparison was plausible. We excluded dental-only, behavioral-only, long-term-services-only, dual-only, foster-care-only, and other specialty programs from the main sample unless they were part of a mainstream comprehensive pharmacy comparison. The source universe contains 103 plan/source rows across 19 states. We classified each row into a no-common-PDL main variation sample, a common/statewide PDL secondary comparison sample, or a stale/currentness-review category.

Formulary sources came from public plan and state pharmacy pages, static PDFs, machine-readable JSON files, spreadsheet PDLs, and two bounded public search-tool extractions where no static comprehensive PDF was located. The finalized source collection included 101 downloaded source rows with supported parsers and two public-tool-backed rows. The full file-backed extraction contains 428,135 formulary rows.

Target drugs were the top 100 Medicaid drugs ranked by 2024 State Drug Utilization Data gross spending.7 We linked extracted formulary rows to these target drugs using parser-specific normalization and conservative token matching. Each plan-drug cell was assigned to one standardized public status category: preferred, preferred with utilization management, nonpreferred, mixed within-plan match, or not covered / not listed / unmatched. Utilization-management indicators included prior authorization, step therapy, quantity limits, and comparable public requirement signals when exposed by the source.

The primary analysis sample contains 74 plan rows and 7,400 plan-drug cells in states without a binding common Medicaid managed care PDL. We summarized status shares by state, within-state plan-pair exact-status agreement, covered-status agreement, and drug-level counts of states with observed within-state variation. The common/statewide PDL rows were analyzed separately after collapsing repeated plan rows that shared the same common source; these results describe cross-state variation in common-PDL policy choices, not within-state plan variation.

Because State Drug Utilization Data product names can be truncated or formulation-like, we preserved the strict token-match panel as the audit trail and added a brand-family sensitivity layer for named examples. In that layer, same-base non-strict rows were included when the base drug name appeared, while broad fragments, criteria text, and separate biosimilar or generic-reference rows were excluded from automatic expansion.

Finally, we added an exploratory PBM/pharmacy-administrator layer for the 74 main-sample rows. Coding used public state materials, plan pharmacy pages, provider materials, and cautious plan-family evidence when state-specific confirmation was not located. High- and medium-confidence rows supported descrip-

tive same-admin pair comparisons; low-confidence and unresolved rows were excluded from the same-admin pair analysis.

This study used public documents and public aggregate drug-utilization data. It did not involve human-subjects data and did not require institutional review board approval.

## Results

Exhibit 1 shows the sample construction. The source universe includes 103 plan/source rows, of which 74 are in the main no-common-PDL variation sample. Seventy-two of these rows are current plan-specific sources and two are public-tool-backed sources. Twenty-eight rows are common/statewide PDL rows retained for secondary cross-state comparison, and one stale Arizona row is retained for currentness review.

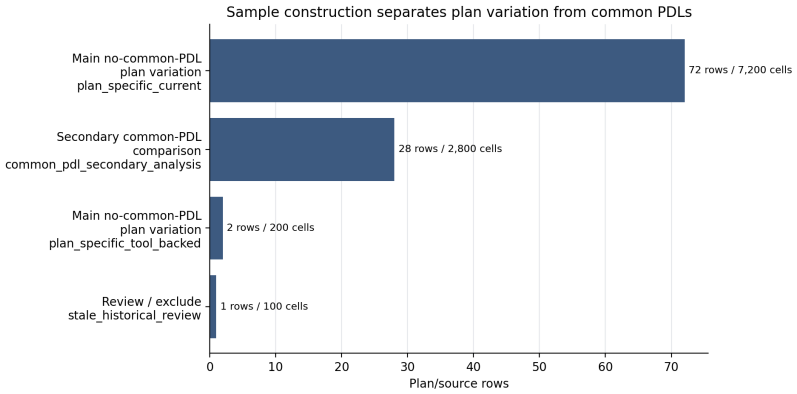


**Figure 1:** Exhibit 1. Medicaid managed care formulary source-governance and analysis sample construction. Source: author analysis of collected public plan and state formulary/PDL sources through May 20, 2026

*Note:* This figure compares estimates across groups or specifications for the manuscript sample construction. It is intended to make effect heterogeneity and subgroup precision easier to assess.

In the 74-plan main sample, 56.0 percent of top-100 plan-drug cells were not covered, not listed, or unmatched; 21.8 percent were preferred with utilization management; 7.8 percent were nonpreferred; 7.6 percent were preferred without utilization management; and 6.8 percent had mixed within-plan matches. Exhibit 2 shows that the distribution varied across states. In some states, not-listed or unmatched cells dominated the public formulary record. In others, nonpreferred placement or preferred-with-UM status accounted for a larger share of the observed differences.

Within-state agreement was far from uniform. Across all 238 within-state plan pairs in the main sample, median exact-status agreement was 0.63. The lowest

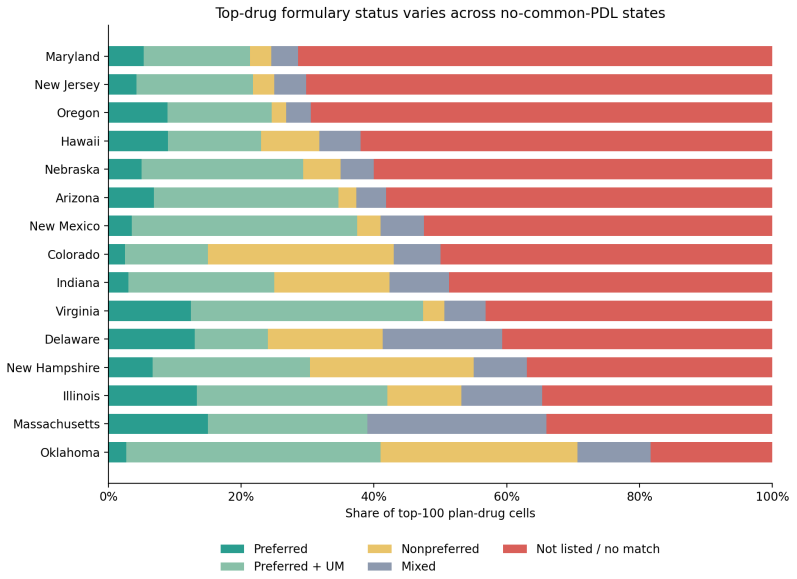


**Figure 2:** Exhibit 2. Main no-common-PDL sample status mix by state for the top 100 Medicaid drugs by 2024 gross spend. Source: author analysis of standardized plan-drug panel

*Note:* This figure presents the manuscript main state status mix. It is included to make the empirical design, sample structure, or headline result easier to read alongside the surrounding text.

state medians appeared in Delaware and Oklahoma (0.42), Nebraska (0.45), Colorado (0.47), and New Hampshire (0.50). Exhibit 3 shows the distribution of within-state exact-status agreement. These statistics are not estimates of clinical access; they measure whether public formularies classify the same high-spend drug the same way across plans in the same state.

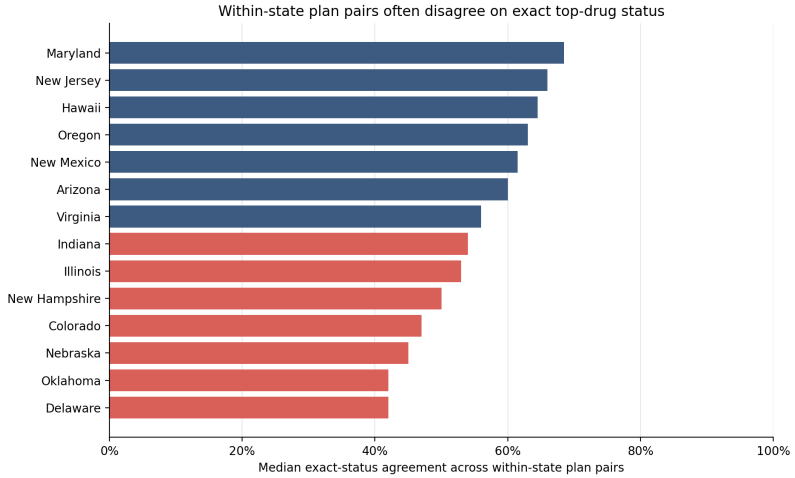


**Figure 3:** Exhibit 3. Within-state plan-pair exact-status agreement for top-100 drugs in the no-common-PDL sample. Source: author analysis of pairwise plan-drug status alignment

*Note:* This figure presents the manuscript within state alignment. It is included to make the empirical design, sample structure, or headline result easier to read alongside the surrounding text.

Drug-level variation appeared repeatedly among high-spend products. Under the brand-family named-example layer, leading examples with repeated within-state variation included Dupixent, Ozempic, Trulicity, Symbicort, Eliquis, Stelara, Cosentyx, Biktarvy, Trikafta, Vraylar, Hemlibra, Suboxone, Humira, Jardiance, Skyrizi, and Sublocade. These examples should be interpreted as public formulary-status examples, not as direct measures of prescription fills, denials, or appeals.

The brand-family sensitivity analysis changed match completeness but not the central interpretation. Strict matching classified 56.0 percent of main-sample cells as not listed or unmatched. Brand-family resolution reduced that share to 42.9 percent, while increasing the preferred-with-UM share from 21.8 percent to 28.5 percent, the nonpreferred share from 7.8 percent to 11.3 percent, and the preferred share from 7.6 percent to 9.1 percent. Exhibit 4 shows the strict-versus-brand-family comparison.

The secondary common-PDL comparison showed a related but distinct pattern. After collapsing repeated common-PDL plan rows to unique state/source/drug

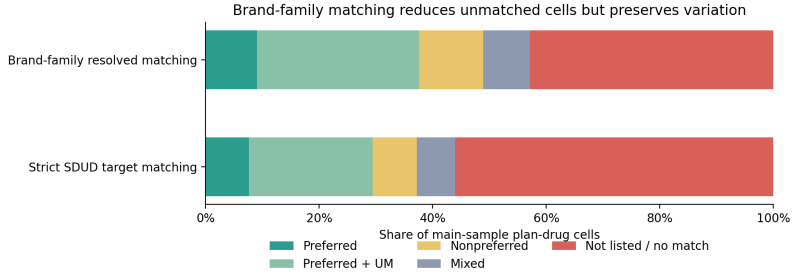


**Figure 4:** Exhibit 4. Strict State Drug Utilization Data target matching versus brand-family resolved matching in the no-common-PDL sample. Source: author analysis of strict and brand-family plan-drug panels

*Note:* This figure reports a robustness or sensitivity check for the manuscript brand family sensitivity. It shows how the main estimate changes under alternative assumptions, samples, or specifications.

cells, common-PDL sources classified 13.2 percent of top-drug cells as preferred, 9.0 percent as preferred with utilization management, 15.8 percent as nonpreferred, 10.8 percent as mixed, and 51.2 percent as not listed or unmatched. This comparison indicates cross-state differences in centralized PDL choices, not within-state plan variation.

The exploratory PBM/pharmacy-administrator layer coded all 74 main-sample plan rows: 31 high confidence, 32 medium confidence, and 11 low confidence or unresolved. Among the 24 usable same-state same-admin plan pairs, median exact-status agreement was 0.815, compared with 0.61 among different-admin or uncoded pairs. Same-admin pairs were therefore more aligned, but not identical. Several same-admin pairs still showed materially different public status rules, including NH Healthy Families versus WellSense in New Hampshire and CareSource versus Managed Health Services in Indiana, both coded to Express Scripts, and Aetna versus Molina in Illinois, coded to CVS Caremark.

## Discussion

This analysis shows substantial public formulary variation in Medicaid managed care states where a common statewide PDL does not fully determine plan status. The most important result is not only that many high-spend drugs were absent from public plan sources under strict matching. It is that plans in the same state often disagreed on whether the same drug was preferred, preferred with utilization management, nonpreferred, mixed, or not listed in the public formulary source.

The consumer implication is straightforward. Medicaid beneficiaries may choose among plans based on provider networks, plan names, or state enrollment materials, while drug coverage information remains harder to compare. If a person

uses a specialty drug, biologic, GLP-1, anticoagulant, HIV medication, or behavioral health medication, plan assignment can become a pharmacy-access event. The administrative burden arises before a denial: families and clinicians must determine which public source applies, whether a drug is listed, and whether prior authorization, step therapy, or quantity limits are visible.

The state oversight implication is also important. Variation is not automatically bad. It may reflect deliberate plan flexibility, different rebate strategies, clinical-management choices, legacy publication systems, or partial state standardization. But large within-state differences for high-spend drugs should be explainable. State Medicaid agencies that permit plan-level pharmacy discretion may need routine monitoring of formulary divergence, public plan-comparison tools that surface drug-level differences, and clearer expectations for how plans publish formulary and utilization-management rules.

The PBM/pharmacy-administrator result sharpens but does not replace the main finding. Same-admin pairs were more similar than other pairs, as expected if shared pharmacy infrastructure creates common templates or defaults. But shared administration did not guarantee identical public PDL outputs. This secondary result should be interpreted cautiously because coding relied on public plan and state materials rather than a full contract audit. Still, it suggests that plan-level accountability and state oversight matter even when pharmacy infrastructure is shared.

The common-PDL comparison offers a policy contrast. Common/statewide PDLs may reduce within-state plan disagreement and simplify beneficiary-facing comparison, but they do not create national uniformity. States with common sources still differed from one another in preferred status, nonpreferred status, and utilization-management signals for high-spend products. The policy choice is therefore not simply uniform versus non-uniform; it is where standardization should occur, how transparent the standardization is, and how exceptions are administered.

This study has limitations. Public formulary sources vary in format, timing, and level of detail. Not-listed or unmatched cells combine true noncoverage, drugs omitted from public documents, and conservative name-matching failures. Brand-family resolution improves clinical recognizability but should not be treated as an NDC-level crosswalk. Public utilization-management signals may omit internal criteria or exception pathways. PBM/pharmacy-administrator coding is exploratory and source-dependent. Finally, this is a descriptive map of public rules, not a causal estimate of how formulary variation changes prescribing, spending, adherence, appeals, or clinical outcomes.

## Conclusion

In Medicaid managed care states without a common PDL, public formularies and PDLs vary substantially across plans for high-spend drugs. This variation is relevant for state oversight, plan accountability, PBM governance, and

beneficiary transparency. A Medicaid plan choice can also be a drug-coverage choice, and public comparison tools should make that fact easier for beneficiaries, providers, and states to see.

## Data Availability

The analysis uses public plan/state formulary sources and public Medicaid State Drug Utilization Data. The source manifest, parser scripts, analysis scripts, and generated review tables are maintained in the project repository. Public release of derived code and nonrestricted source metadata is planned after final source-currentness review.

## Funding

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## Conflicts Of Interest

The author reports no conflicts of interest.

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